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# Essays in Economic Growth and Development

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## ESSAYS IN ECONOMIC GROWTH AND DEVELOPMENT

# ESSAYS IN ECONOMIC GROWTH AND DEVELOPMENT

A dissertation submitted in partial fulfillment  
of the requirements for the degree of  
Doctor of Philosophy in Economics

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## ABSTRACT

This dissertation consists of three chapters exploring the *Solow Residual* of the Solow growth model. Two central components of the *Solow Residual* have been studied in my doctoral dissertation. The first is the structural transformation, an *internal* adjustment process that helps the economy attain the optimal points on its *Production Possibility Frontier* by reallocating resources from the low-productivity sectors to the high-productivity sectors. The second is the technology diffusion, a positive *externality* process that pushes forward the economy's *Production Possibility Frontier* if it adopts the newer technology.

The first chapter of my dissertation is devoted to a case study of China's structural transformation. As one of the fastest growing economies in the world, China has observed dramatic reallocation of resources from the agricultural sector to the nonagricultural sector over the last three decades. This chapter proposes a two-sector growth model and identifies three driving forces for China's structural transformation. Most importantly, the migration costs can be shown as a significant barrier to the reallocation process after I calibrate the model with real data. The second and the third chapters of my dissertation are devoted to the study of the technology diffusion. The second chapter is a collaborative effort with Gary Ferrier and Javier Reyes. We approach the cross-country technology diffusion from a novel perspective – the trade network can be viewed as the conduit of the technology diffusion. The question we ask is whether the trade network structure matters in the technology diffusion process. We consider 24 major technologies over the period from 1962 to 2000 and find that, in most cases, there is strong and robust evidence to suggest that the better-connected countries on the trade network tend to adopt or assimilate newer and more advanced technologies faster. However, the better-connected countries tend to have lower technology intensity if the technology has become obsolete. Finally,

the third chapter is a theoretical approach to the technology diffusion. In particular, the technology diffusion across countries can be generalized as a learning process on networks. Based on a stylized learning model, this chapter examines the impact of the network structures on the speed of the diffusion process.

## **ACKNOWLEDGEMENTS**

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Last but definitely not least, this dissertation and my graduate study would not have been possible without the constant love and support of my wife, Longyan, and my parents, Zhiwen and Zhenghuai.

## **DEDICATION**

To my wife, Longyan, and my parents.

## TABLE OF CONTENTS

I. INTRODUCTION .....	1
II. CHAPTER 1 .....	3
THE ROLE OF THE MIGRATION COSTS IN CHINA'S STRUCTURAL TRANSFORMATION.....	3
2.1 Introduction.....	3
2.2 The Model .....	9
2.2.1 Technology (Labor Productivity versus Total Factor Productivity).....	9
2.2.2 Consumer's Problem.....	11
2.2.3 Migration Decision .....	12
2.2.4 Firm's Problem .....	14
2.2.5 Market Clearing .....	15
2.2.6 Equilibrium .....	15
2.2.7 Qualitative Analysis.....	16
2.3 Numerical Exercises .....	16
2.3.1 Calibration.....	16
2.3.2 Counterfactual Exercises .....	17
2.4 Policy Implications .....	19
2.5 Conclusion .....	20
References .....	28



Appendix.....	30
III. CHAPTER 2 .....	32
TECHNOLOGY DIFFUSION ON THE INTERNATIONAL TRADE NETWORK.....	32
3.1 Introduction.....	32
3.2 Literature Review.....	35
3.2.1 Why Is Technology Diffusion Important?.....	36
3.2.2 Technology Diffusion in Theory .....	37
3.2.3 Technology Diffusion in Practice .....	39
3.2.4 Network Effects on Technology Diffusion.....	42
3.3 Trade Network and Technology Data.....	45
3.4 Empirical Model and Results.....	52
3.5 Concluding Remarks.....	58
References.....	67
Appendix A.....	71
Appendix B .....	73
IV. CHAPTER 3 .....	74
LEARNING ON NETWORKS .....	74
4.1 Introduction.....	74
4.2 Basic Learning Model.....	75
4.2.1 The Building Blocks .....	75

4.2.2 The Initial Conditions .....	76
4.2.3 The Naïve Learning Algorithm.....	76
4.2.4 Analytical and Simulation Results.....	78
4.3 Network Properties of the Square Lattice .....	79
4.4 Learning on a Square Lattice .....	82
4.4.1 The Building Blocks .....	82
4.4.2 The Initial Conditions .....	83
4.4.3 The Modified Learning Algorithm .....	83
4.4.4 The Simulation Results .....	84
4.5 Conclusion .....	85
References .....	92
V. CONCLUSION .....	93

## **LIST OF PAPERS**

Zhu, Z., Ferrier, G., and Reyes, R (2013) “Technology Diffusion on the International Trade Network,” Preparing for Publication Submission.

## I. INTRODUCTION

This dissertation represents my first endeavors into exploring the *Solow Residual* of the Solow growth model. Traditionally, the *Solow Residual* is a “black box” and can be freely interpreted as any contributing factors to the economic growth other than capital and labor inputs. The dissertation is focused on two possible components of the *Solow Residual*. The first is the structural transformation, an *internal* adjustment process that helps the economy attain the optimal points on its *Production Possibility Frontier* by reallocating resources from the low-productivity sectors to the high-productivity sectors. The second is the technology diffusion, a positive *externality* process that pushes forward the economy’s *Production Possibility Frontier* if it adopts the newer technology.

The first chapter of my dissertation is devoted to a case study of China’s structural transformation. As one of the fastest growing economies in the world, China has observed dramatic reallocation of resources from the agricultural sector to the nonagricultural sector over the last three decades. This chapter proposes a two-sector growth model and identifies three driving forces for China’s structural transformation. Most importantly, the migration costs can be shown as a significant barrier to the reallocation process after I calibrate the model with real data. The second and the third chapters of my dissertation are devoted to the study of the technology diffusion. The second chapter is a collaborative effort with Gary Ferrier and Javier Reyes. We approach the cross-country technology diffusion from a novel perspective – the trade network can be viewed as the conduit of the technology diffusion. The question we ask is whether the trade network structure matters in the technology diffusion process. We consider 24 major technologies over the period from 1962 to 2000 and find that, in most cases, there is strong and

robust evidence to suggest that the better-connected countries on the trade network tend to adopt or assimilate newer and more advanced technologies faster. However, the better-connected countries tend to have lower technology intensity if the technology has become obsolete. The two findings together confirm the assumptions of the quality-ladder models in which old (lower quality) products are constantly being replaced by new (higher quality) products. Finally, the third chapter is a theoretical approach to the technology diffusion. In particular, the technology diffusion across countries can be generalized as a learning process on networks. By developing the stylized learning models, this chapter investigates two obstructions to the learning process. First, the learning process can be obstructed if the agents are too “stubborn” and put too much weight on themselves. Second, the learning process can be obstructed if the agents are too “far away” from others on the network.

## II. CHAPTER 1

# THE ROLE OF THE MIGRATION COSTS IN CHINA'S STRUCTURAL TRANSFORMATION

## 2.1 Introduction

Over the last three decades, China has achieved breathtaking economic development and growth. Between 1978 and 2008, China's real GDP per capita grew at an average rate of 8.7% per year<sup>1</sup>. Along with the dramatic improvement of the standards of living of the Chinese people, another key fact of China's development process is the structural transformation<sup>2</sup>. The structural transformation, whereby the output and employment share of the agricultural sector is replaced by the manufacturing sector at the first stage and by the service sector at the second stage, has long been observed in economic history and documented in the literature as the Kuznets facts (Kuznets, 1966). In contrast with the Kaldor facts, which emphasize the long term constancy of the "Great Ratios,"<sup>3</sup> the Kuznets facts feature the nonbalanced growth and the massive resource reallocation among different sectors (Acemoglu, 2008).

The counterparts of the agricultural, manufacturing, and service sectors in China's official statistical reports are the primary (farming, forestry, animal husbandry, fishing and

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<sup>1</sup> Data source: *China Statistical Yearbook 2009*, National Bureau of Statistics of China. Throughout the chapter, the only data source is the official statistics in *China Statistical Yearbook 2009*. Some necessary adjustments and calculations are also based on the official source. Discussion on the reliability of China's official statistics appears in Young (2003), Holz (2006), and Brandt, Hsieh, and Zhu (2008).

<sup>2</sup> In broad sense, the structural transformation refers to changes in the organization and efficiency of production accompanying the process of development (Acemoglu, 2008). In this chapter, however, the structural transformation only refers to the downsizing agricultural sector and the upsizing nonagricultural sector.

<sup>3</sup> The "Great Ratios" include the growth rate of per capita GDP, the capital to output ratio, the real interest rate, and the shares of capital and labor in national income (Kaldor, 1961).

relevant services), secondary (mining, manufacturing, utilities, and construction), and tertiary sectors (everything else), respectively. After 1978, the output (real GDP) share of the primary sector declined from 41% in 1978 to only 10% in 2008, while the output shares of the secondary and tertiary sectors increased from 30% to 49% and from 29% to 41%, respectively (see Figure 1). When it comes to the sectoral share of employment, there are similar patterns developing; these patterns are that the primary sector was gradually being replaced by the secondary and tertiary sectors. The employment share of the primary sector was approximately 70% in 1978. However, it accounted for less than 40% in 2008 (see Figure 2). Since there is a clear trend for the secondary (manufacturing) sector to continue to prosper in the near future<sup>4</sup>, in terms of both the output share and the employment share, it can be argued that China is still at the first stage of structural transformation. Therefore, throughout the rest of this chapter, it can be assumed that the China's economy has only two sectors: the agricultural sector (primary) and the nonagricultural sector (secondary and tertiary). As a result, this chapter is concerned with how the labor forces in the agricultural sector have been transferring over time to the nonagricultural sector. However, within the nonagricultural sector, how resources are reallocated between the manufacturing sector and the service sector or between the public sector and the private sector is beyond the purpose of this chapter<sup>5</sup>.

[Insert Figures 1 and 2 here]

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<sup>4</sup> Industrial countries' experience shows that the manufacturing sector follows a hump-shape pattern during the structural transformation process, i.e., the size of the manufacturing sector first increased but then decreased.

<sup>5</sup> Further dichotomy within the nonagricultural sector: For the manufacturing sector versus the service sector, see Echevarria (1997), Kongsamut, Rebelo, and Xie (2001), and Duarte and Restuccia (2007, 2010); For China's public sector versus its private sector, see Dekle and Vandenbroucke (2006), Brandt, Hsieh, and Zhu (2008), and Song, Storesletten, and Zilibotti (2009).

The main objective of this chapter is to identify the most contributing factors of China's structural transformation during the post-reform period. In the literature, two major factors of the structural transformation have been acknowledged. On the one hand, some argue that the productivity growth in the nonagricultural sector plays the dominating role in the process of structural transformation. The productivity growth in the nonagricultural sector (also referred as the urban or modern sector) raises the marginal product of labor (wages) and attracts the excess labor forces from the agricultural sector. For instance, in Lewis's (1954) reasoning, the wage difference between the two sectors is what triggers the "unlimited" supplies of the rural labor forces to the urban areas. Harris and Todaro (1970) follow Lewis's reasoning. However, they flavor this theory with the possibility of unemployment in the nonagricultural sector. More recently, Hansen and Prescott (2002) attribute the transition from constant to growing living standards and the structural transformation to the superior productivity, "Solow technology", in the nonagricultural sector.

On the other hand, some argue that the productivity growth in the agricultural sector plays the dominating role. Based on the universally observed empirical evidence, Engel's law, the demand for agricultural goods has a lower income elasticity than that for nonagricultural goods. Hence, the agricultural productivity growth helps release labor forces for the nonagricultural sector after the subsistence level of agricultural goods has been met. For example, Matsuyama (1992) assumes Engel's type preference and finds that the employment share of the agricultural sector is a decreasing function of the total factor productivity (TFP) in the agricultural sector. Moreover, Caselli and Coleman (2001) interpret the faster productivity growth in the agricultural sector relative to other sectors as the engine of the structural



transformation of the United States over the last century. Finally, Gollin, Parente, and Rogerson (2002) conclude that the higher productivity in the agricultural sector is the prerequisite of industrialization.

It can be summarized so far that the agricultural productivity growth “pushes” and the nonagricultural productivity growth “pulls” the labor forces out of the agricultural sector (Gylfason and Zoega, 2006; Alvarez-Cuadrado and Poschke, 2009). In the case of China, the productivities in both the agricultural and nonagricultural sectors have achieved steady growth<sup>6</sup> over the post-reform era (see Figure 3). Therefore, this chapter examines productivity growth in both sectors during China’s structural transformation.

[Insert Figure 3 here]

This chapter contributes to the literature by focusing on another contributing factor of China’s structural transformation: the reduction of the migration costs<sup>7</sup>. The migration costs prevent labor forces from moving freely between sectors. In China, one of the most prominent migration costs is the opportunity cost mandated by the *Hukou* system, which states that people only have access to housing, education, and other important social services based upon their registered places. Furthermore, the *Hukou* system functions as an internal passport system in

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<sup>6</sup> The only exception is the temporary drop by the end of 1980s which was mainly caused by the political turmoil in the year of 1989.

<sup>7</sup> In analyzing the structural transformation at the early stage, it is common in the literature that “agricultural” is equivalent to “rural” and “nonagricultural” is equivalent to “urban.” However, nonagricultural activities exist and play a more and more important role in rural China. The nonagricultural share of rural employment grew dramatically from 9.2% in 1978 to 43.2% in 2008. This empirical evidence does not make the current model inappropriate. Since the *Hukou* system is just one of the migration costs, even if labor forces switch to nonagricultural jobs by staying in rural, “migration” costs still apply.

China (Cai, Park, and Zhao, 2008). Other significant migration costs include transportation cost, psychological cost, search cost, and so forth (Knight and Song, 1999). Many empirical studies claim that the migration costs in China play an important role in discouraging people from moving to the nonagricultural sector (Knight and Song, 1999; Cai, Park, and Zhao, 2008; Lee and Meng, 2010). This chapter, however, is the first attempt to explicitly model the effects of the migration costs on the process of structural transformation.

This chapter is closely related to the large body of literature on the structural transformation. To qualitatively analyze each factor's contribution to China's structural transformation, this chapter develops a simple two-sector model with a migration-decision feature. Specifically, this chapter assumes nonhomothetic preference, which is characterized in the demand side tradition of the structural transformation theory (Kongsamut, Rebelo, and Xie, 2001). Also, the productivity growth can be considered as a source of the structural transformation, which is the supply side tradition of the structural transformation theory (Ngai and Pissarides, 2007; Acemoglu and Guerrieri, 2008). In combining both the demand side and supply side traditions, this chapter is following Gollin, Parente, and Rogerson (2002), Rogerson (2008), Duarte and Restuccia (2007, 2010), and Alvarez-Cuadrado and Poschke (2009). This chapter differs from the above literature in that it emphasizes the migration costs while most of the above literature makes the assumption of perfect mobility of factors. With respect to studying the China's economy, this chapter is similar to Dekle and Vandenbroucke (2006) and Brandt, Hsieh, and Zhu (2008). For instance, Dekle and Vandenbroucke (2006) admit the productivity growths in both the agricultural and nonagricultural sectors as the contributing factors, as does this chapter. However, they identify the third contributing factor as the reduction of the government share in GDP rather than the reduction of the migration costs. Brandt, Hsieh, and

Zhu (2008), on the other hand, like this chapter, take into account the barrier to labor mobility in China. But they use the wage gap as the proxy of labor barrier while this chapter explicitly models the migration costs.

Based on the current model, numerical exercises are carried out to quantify each source's contribution to China's structural transformation. The National Bureau of Statistics of China reports the GDP at current prices and the real GDP growth rates at both national level and sectoral level. This chapter uses the two sets of time series to calculate both the real sectoral labor productivity and the nominal sectoral labor productivity<sup>8</sup>, which can be further used to match the equilibrium of the model with the salient features of China's structural transformation during the period from 1978 to 2008. The historical data also uncovers the 30.9% total reduction of the agricultural share of employment during this period while the calibrated benchmark model captures the 30.0% total reduction of the agricultural share of employment during the same period. However, the counterfactual results of this chapter reveal that, without the agricultural productivity growth, the reduction rate of the agricultural share of employment would be only 11.0%; without the nonagricultural productivity growth, the reduction rate would still be 28.6%. Finally, without the migration costs, the reduction rate would be 40.1% and the net contribution would be 10.1% if compared with the benchmark model. Therefore, the main contributing factors of China's structural transformation are the agricultural productivity growth and the reduction of the migration costs. The nonagricultural productivity growth has relatively little impact on this process.

The rest of the chapter is organized as follows: Section 2.2 presents a simple two-sector model. By including the migration-decision feature, the model takes into account all the three

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<sup>8</sup> Refer to Appendix for details.

contributing factors of China's structural transformation: the agricultural productivity growth, the nonagricultural productivity growth, and the reduction of the migration costs. To quantify each factor's contribution, Section 2.3 first calibrates the model with China's real data and then conducts a series of counterfactual exercises to identify the most contributing sources of China's structural transformation. Section 2.4 interprets some policy implications from the results in Section 2.3. Finally, Section 2.5 concludes this chapter.

## 2.2 The Model

The model assumes a two-sector closed China's economy. The economy consists of an agricultural sector producing the agricultural goods and a nonagricultural sector providing the composite goods of industrial commodities and services.

### 2.2.1 Technology (Labor Productivity versus Total Factor Productivity)

The productivity can be either the labor productivity or the TFP. The fundamental difference between the two is that the labor productivity is defined as the real output per unit of labor input; whereas, the TFP is defined as the real output per unit of all inputs, often including both labor and capital. However, the two concepts of productivity are closely related. Consider the following Cobb-Douglas type production function:

$$Y = TFP \cdot K^{1-\beta} \cdot L^{\beta} \quad 0 < \beta < 1$$

where  $Y$  is the real output;  $TFP$  is the total factor productivity;  $K$  is the capital input; and  $L$  is the labor input.

Consider the notation that the capital to labor ratio is  $k = \frac{K}{L}$ , the preceding equation can be rewritten as:

$$Y = TFP \cdot k^{1-\beta} \cdot L$$

Denote the labor productivity as  $A$ , it can be solved as:

$$A = \frac{Y}{L} = TFP \cdot k^{1-\beta}$$

Therefore, the labor productivity is essentially a function of the TFP. In fact, they are both the measures of productivity. But the labor productivity has an obvious advantage: it is easy to compute. However, the estimation of the TFP requires the growth accounting techniques and much more data.

To take advantage of the empirical convenience, this chapter uses only the labor productivity as the measure of productivity, which captures the technology level, the capital intensity and other residual factors.

At each period, two types of goods, the agricultural goods ( $a$ ) and the composite goods of industrial commodities and services ( $n$ ), are produced according to the following constant returns to scale production functions (as in Duarte and Restuccia, 2007, 2010):

$$Y_t^i = A_t^i L_t^i, \quad i \in \{a, n\}, \quad \text{and } A_t^i > 0,$$

where  $Y_t^i$  is the output in sector  $i$ ;  $L_t^i$  is the labor input in sector  $i$ ; the total labor force is constant over time and normalized to 1 so that  $L_t^a + L_t^n = 1$ ; and  $A_t^i$  is the labor productivity in sector  $i$ .

### 2.2.2 Consumer's Problem

Consumers are infinitely lived and have identical preferences. Their nonhomothetic preferences are given by (as in Gollin, Parente, and Rogerson, 2002):

$$U(C_t^a, C_t^n) = \begin{cases} \ln(C_t^n) + \bar{C}^a & \text{if } C_t^a \geq \bar{C}^a \\ C_t^a & \text{if } C_t^a < \bar{C}^a \end{cases} \quad (1)$$

where  $C_t^a$  and  $C_t^n$  denote the aggregate<sup>9</sup> consumption of goods  $a$  and goods  $n$ , respectively.  $\bar{C}^a$  is a positive constant, which captures the Engel's law, i.e., the economy switches to the consumption of industrial commodities and services once its subsistence level consumption of agricultural goods,  $\bar{C}^a$ , is satisfied.

At each period, the representative household inelastically supplies its one unit of labor endowment and chooses its consumption bundle to maximize the present value of (1), which is discounted at a rate of  $0 < \beta < 1$  and is subject to the budget constraint:

$$\max \begin{cases} \sum_{t=0}^{\infty} \beta^t (\ln(C_t^n) + \bar{C}^a) & \text{s.t. } w_t^a(1 - L_t^n) + w_t^n L_t^n = p_t^a \bar{C}^a + p_t^n C_t^n & \text{if } C_t^a \geq \bar{C}^a \\ \sum_{t=0}^{\infty} \beta^t (C_t^a) & \text{s.t. } w_t^a \cdot 1 = p_t^a C_t^a & \text{if } C_t^a < \bar{C}^a \end{cases} \quad (2)$$

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<sup>9</sup> Since the consumers are identical, variables can be aggregated simply by replacing lower case by upper case letters.

where  $w_t^i$  is the nominal wage in sector  $i$ ;  $p_t^i$  is the price of good  $i$ ; and  $L_t^n$  represents the labor input in the nonagricultural sector.

### 2.2.3 Migration Decision

To maximize utility, the economy will devote the entire one unit of the labor force into the agricultural sector when  $C_t^a < \bar{C}^a$ . Once the output in the agricultural sector reaches  $\bar{C}^a$ , ideally, all the excess labor force will be reallocated from the agricultural sector to the nonagricultural sector.

However, a key assumption here is that the labor force cannot move freely between the two sectors. In other words, migration incurs costs, which, in the case of China, include psychological cost, opportunity cost, transportation cost, search cost, etc. At each period, the excess labor force makes the following decision to migrate or not to migrate:

$$\begin{cases} \text{migrate} & \text{if } \frac{w_t^n - w_t^a}{w_t^a} - Q > 0 \\ \text{not to migrate} & \text{if } \frac{w_t^n - w_t^a}{w_t^a} - Q \leq 0 \end{cases} \quad (3)$$

where  $Q$  denotes the migration costs. It is assumed that excess laborers have heterogeneous values of  $Q$ , since the migration costs differ from one person to another. It is also analytically convenient to assume that  $Q$  is distributed according to a Pareto function:

$$PDF: f(Q|\mu, \delta) = \frac{\mu \delta^\mu}{Q^{\mu+1}}; \quad \delta \leq Q < \infty; \mu, \delta > 0$$

$$CDF: f(Q|\mu, \delta) = 1 - \left(\frac{\delta}{Q}\right)^\mu; \quad \delta \leq Q < \infty; \mu, \delta > 0$$

Therefore, the probability that  $Q$  is greater than  $\frac{w_t^n - w_t^a}{w_t^a}$  is:

$$Prob\left(Q > \frac{w_t^n - w_t^a}{w_t^a}\right) = \left(\frac{\delta}{\left(\frac{w_t^n - w_t^a}{w_t^a}\right)}\right)^\mu$$

And the probability that the excess labor force chooses to migrate is:

$$Prob(migrate) = 1 - Prob\left(Q > \frac{w_t^n - w_t^a}{w_t^a}\right) = 1 - \left(\frac{\delta}{\left(\frac{w_t^n - w_t^a}{w_t^a}\right)}\right)^\mu$$

Once the output in the agricultural sector reaches  $\bar{C}^a$ , the agricultural labor required can be calculated as:

$$\bar{L}_t^a = \frac{\bar{C}^a}{A_t^a} \quad (4)$$

The migrant labor force at period  $t$  is solved as:

$$M_t = Prob(migrate) \cdot (L_t^a - \bar{L}_t^a) = \left[1 - \left(\frac{\delta}{\left(\frac{w_t^n - w_t^a}{w_t^a}\right)}\right)^\mu\right] \left(L_t^a - \frac{\bar{C}^a}{A_t^a}\right) \quad (5)$$

It also follows that:



$$L_{t+1}^a = L_t^a - M_t \quad (6a)$$

$$L_{t+1}^n = L_t^n + M_t \quad (6b)$$

#### 2.2.4 Firm's Problem

By assumption, when  $C_t^a < \overline{C^a}$ , there is only the agricultural sector in the economy. On the other hand, when  $C_t^a \geq \overline{C^a}$ , there is a continuum of representative firms in each sector. Firms in each sector are competitive in both the factor and output market. At each period, the objective function for the nonagricultural firms is:

$$\max \quad p_t^n A_t^n L_t^n - w_t^n L_t^n \quad (7a)$$

And the optimality condition is:

$$w_t^n = p_t^n A_t^n$$

For the agricultural firms, the output is fixed at  $\overline{C^a}$ , and the labor force is over-employed because of the migration costs. At each period, the objective for the agricultural firms is:

$$\max \quad p_t^a A_t^a \overline{L_t^a} - w_t^a L_t^a \quad (7b)$$

And the optimality condition is:

$$w_t^a = p_t^a A_t^a \left( \frac{\bar{L}_t^a}{L_t^a} \right)$$

Notice that without the migration costs the optimality condition would be  $w_t^a = p_t^a A_t^a$ .

### 2.2.5 Market Clearing

When  $C_t^a \geq \bar{C}^a$ , firms' aggregate demand for labor force must equal the aggregate supply of the economy, which is fixed at 1:

$$L_t^a + L_t^n = 1 \quad (8)$$

Consumers' aggregate consumption for each type of goods must equal the aggregate output in each sector:

$$\bar{C}^a = \bar{Y}^a \quad \text{and} \quad C_t^n = Y_t^n \quad (9)$$

### 2.2.6 Equilibrium

When  $C_t^a \geq \bar{C}^a$ , given the subsistence level consumption  $\bar{C}^a$ , the equilibrium of the economy is a set of prices  $\{p_t^a, p_t^n, w_t^a, w_t^n\}$ , such that: (a) Given  $\bar{C}^a$ , the required agricultural labor force  $\bar{L}_t^a$  is determined; (b) Given prices and  $\bar{L}_t^a$ , the migrant labor force in (5) and the allocation  $\{L_t^a, L_t^n\}$  are determined; (c) Given prices, firm's problem in (7a) and (7b) can be solved under the allocations  $\{L_t^a, L_t^n\}$ ; (d) Given the allocation  $\{L_t^a, L_t^n\}$ , the allocation  $\{C_t^n\}$  is determined; (e) Given prices, consumer's problem in (2) can be solved under the allocations  $\{C_t^n\}$ ; and (f) Markets clear, i.e., (8) and (9) hold.

### 2.2.7 Qualitative Analysis

So far, the three contributing factors of China's structural transformation have all been incorporated by the model. First, the agricultural share of employment is a decreasing function of the labor productivity growth in the agricultural sector, the "labor push" effects. As in (4), the required agricultural labor becomes smaller and smaller when the agricultural productivity grows over time. Second, the agricultural share of employment is a decreasing function of the labor productivity growth in the nonagricultural sector, the "labor pull" effects. As in (5), the probability of migration gets higher when nonagricultural wages increase, which is the result of increasing nonagricultural productivity. Finally, the agricultural share of employment is a decreasing function of the reduction of the migration costs. As in (3), all excess labor force will migrate to the nonagricultural sector if the migration costs  $Q = 0$ .

## 2.3 Numerical Exercises

### 2.3.1 Calibration

In this section, the two-sector model is calibrated with China's real data during the post-reform period from 1978 to 2008. The dynamics of the economy is governed by the migration function (5), which determines the reallocation of labor forces according to 6(a) and 6(b). Suppose that each period in the model is one year. The time series ready for use include,  $\{A_t^a, A_t^n\}$  as the real labor productivity in both sectors (see Figure 3), and the relative-nominal-wage-gap  $\left\{ \frac{w_t^n - w_t^a}{w_t^a} \right\}$ , where  $w_t^i$  is the nominal labor productivity<sup>10</sup> in sector  $i$  (see Figure 4). Therefore, this chapter only needs to calibrate the values of the Pareto function parameters  $\{\mu, \delta\}$ , such that  $\bar{C}^a$  is computed to match the initial values of the agricultural share of employment in

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<sup>10</sup> Refer to Appendix for calculation details.

1978 and 1979, and the calibrated agricultural share of employment has the minimum deviation from the real data.

[Insert Figure 4 here]

The calibrated results are shown in Figure 5, with the calibrated parameters  $\hat{\delta} = 0.04$ ,  $\hat{\mu} = 0.01$ , and  $\bar{C}^a = 1312.8$ . It turns out that the simple two-sector model tracks the real data very well.

[Insert Figure 5 here]

### 2.3.2 Counterfactual Exercises

The next step is to use the calibrated benchmark model to quantify the three factor's contribution to China's structural transformation respectively. Nonetheless, the quantification strategy differs for each factor because of the limited data. For example, the data on how much the migration costs have been reduced or increased over time does not exist. However, the effects of the migration costs can be seen by comparing the benchmark model with the counterfactual model without the migration costs (see Figure 6).

[Insert Figure 6 here]

For the labor productivity growth in the agricultural sector, the counterfactual exercise is to keep the labor productivity in the agricultural sector constant at the 1978 level (see Figure 7).

[Insert Figure 7 here]

Finally, for the labor productivity growth in the nonagricultural sector, the counterfactual exercise is to keep the relative-nominal-wage-gap constant at the minimum level,  $\frac{w_t^n - w_t^a}{w_t^a} = 2.76$ , for all  $t$  (see Figure 8). Recall that the effects of the nonagricultural productivity are embodied in the relative-nominal-wage-gap since the higher nonagricultural productivity tends to widen the gap, which in turn increases the probability of migration.

[Insert Figure 8 here]

The results of the counterfactual exercises are summarized in Table 1. The main contributing factor of China's structural transformation is the agricultural productivity growth. Without the agricultural productivity growth, 19.0% less agricultural labor forces migrate to the nonagricultural sector. The least contributing factor is the nonagricultural productivity growth. If in the absence of the nonagricultural productivity growth, nearly the same percentage migrates, with the tiny difference being 1.4%. Finally, the contribution of the reduction of the migration costs is significant and comparable to that of the agricultural productivity growth. However, the contribution should be interpreted differently. The agricultural share of employment will be reduced by 40.1% if allowing free labor mobility, which means that the migration costs prevent 10.1% labor forces from moving. And the 10.1% potential reduction of the agricultural employment is interpreted here as the contribution of the reduction of the migration costs.

[Insert Table 1 here]

## 2.4 Policy Implications

There are two policy implications following the numerical exercises:

1) The agricultural productivity growth is the most important factor of the structural transformation in China<sup>11</sup>. Another evidence for the “labor push” theory is shown in Figure 9. After ruling out the effects of population growth, the real production in the agricultural sector is fairly stable over time by comparing it with that in the nonagricultural sector. At the same time, another source of China’s structural transformation, the nonagricultural productivity growth, plays an insignificant role in “pulling” labor out of the agriculture. However, in terms of magnitude, the nonagricultural productivity growth is much larger than the agricultural productivity growth (see Figure 3). Thus, the government of China could accelerate the process of structural transformation by strengthening the agricultural productivity growth. This will stimulate the aggregate economic growth not only by having a more productive agricultural sector but also by transferring more laborers to the already highly productive nonagricultural sector.

[Insert Figure 9 here]

2) The migration costs have significant effects on China’s structural transformation, which is likely to be true for other developing countries as well. The counterfactual exercise

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<sup>11</sup> This finding coincides with that in Dekle and Vandenbroucke (2006) and Brandt, Hsieh, and Zhu (2008), and more generally in the setting of developing countries, Gollin, Parente, and Rogerson (2002).

shows that more than 10% agricultural labor forces could have migrated to the nonagricultural sector without the migration costs. Therefore, another approach for the government of China to speed up the structural transformation process is to lower the migration costs, perhaps, with the reform of the *Hukou* system at the top of the list.

In summary, based on the model, the government of China could further realize the potential of the structural transformation either by promoting the agricultural productivity or by reducing the migration costs. The former approach is mainly subject to the technological constraints while the latter is mainly subject to the institutional constraints. Since it takes longer for the technological change to occur, in the short run, more efforts should be devoted into lowering the migration costs.

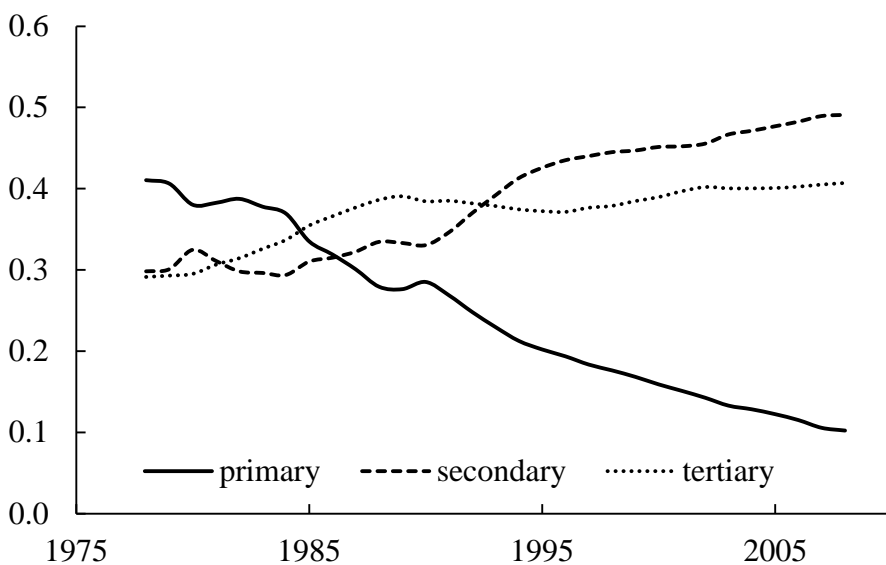
## **2.5 Conclusion**

This chapter documents a number of salient features of China's structural transformation over the post-reform era. A simple two-sector model is added with a migration-decision feature to acknowledge three contributing factors of China's structural transformation: the agricultural productivity growth, the nonagricultural productivity growth, and, particularly, the reduction of the migration costs. In order to quantify each source's contribution to China's structural transformation, this chapter calibrates the model with real data and conducts a series of counterfactual exercises. The findings are that the most contributing factors of China's structural transformation are the agricultural productivity growth and the reduction of the migration costs while the nonagricultural productivity growth plays a marginal role. Given the significant effects of the agricultural productivity growth and the reduction of the migration costs, the government

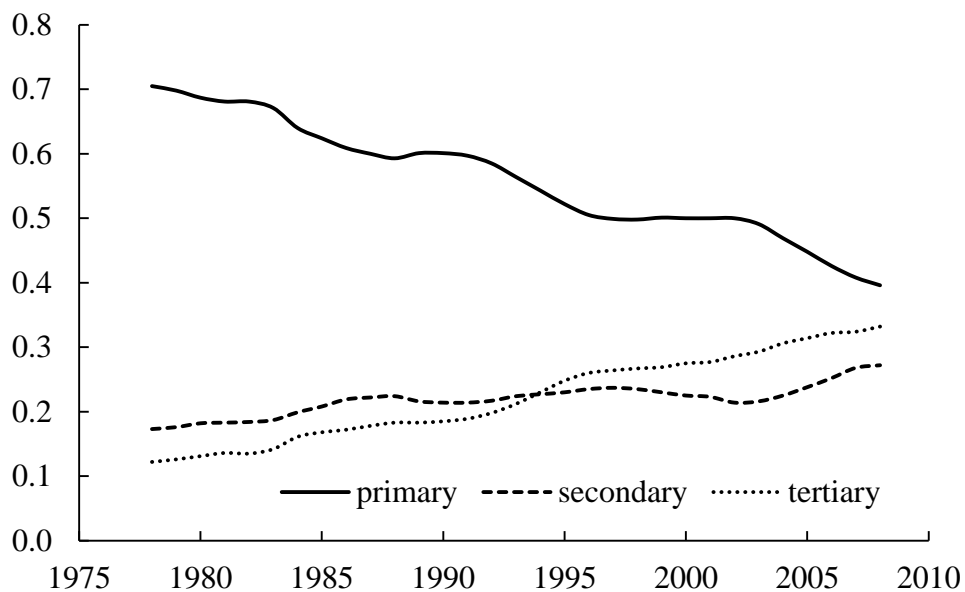
of China could speed up the structural transformation process either by enhancing the agricultural productivity or by lowering the migration costs.



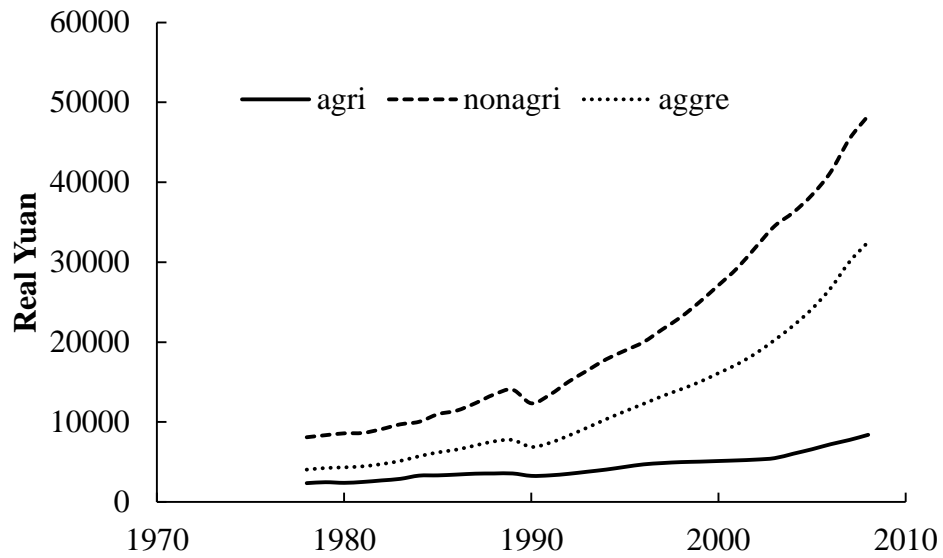
**Figure 1. Sectoral share of real GDP in China, 1978-2008.** The base year is 2005. See Appendix for details of calculating real GDP in China.



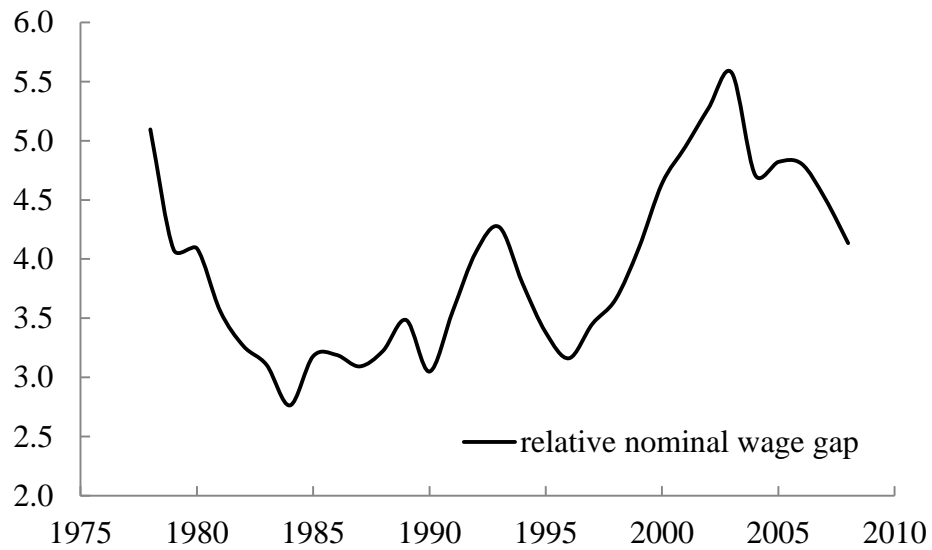
**Figure 2. Sectoral share of employment in China, 1978-2008.**



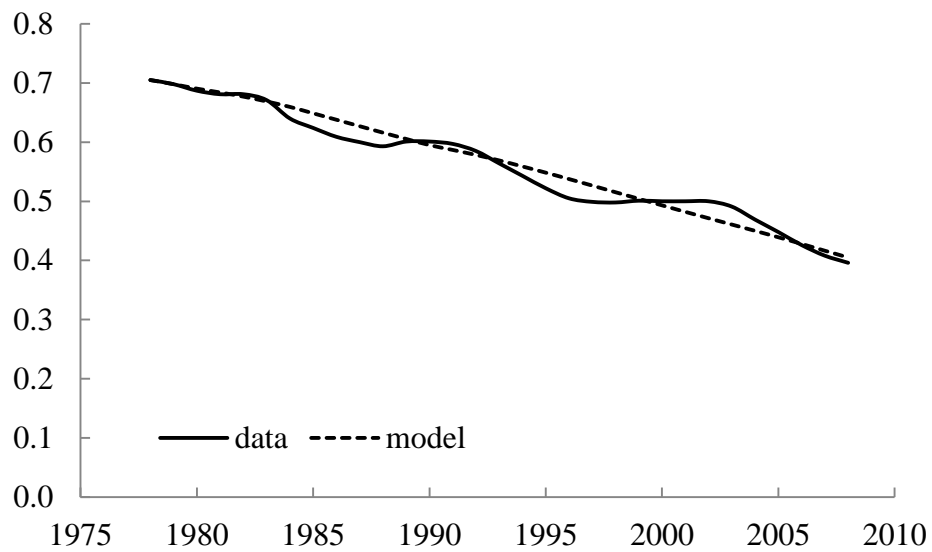
**Figure 3. Real labor productivity in China, 1978-2008.** See Appendix for details of calculation.



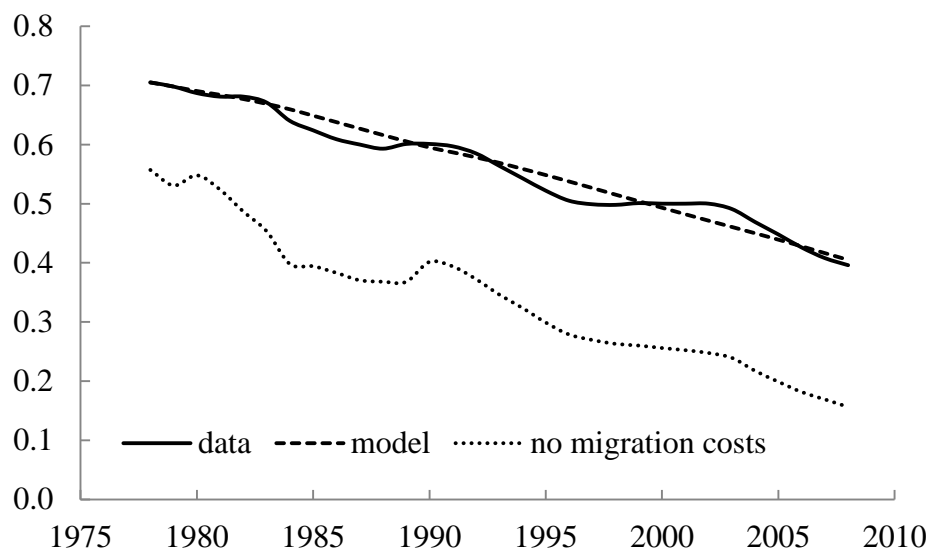
**Figure 4. Relative nominal wage gap in China, 1978-2008.**



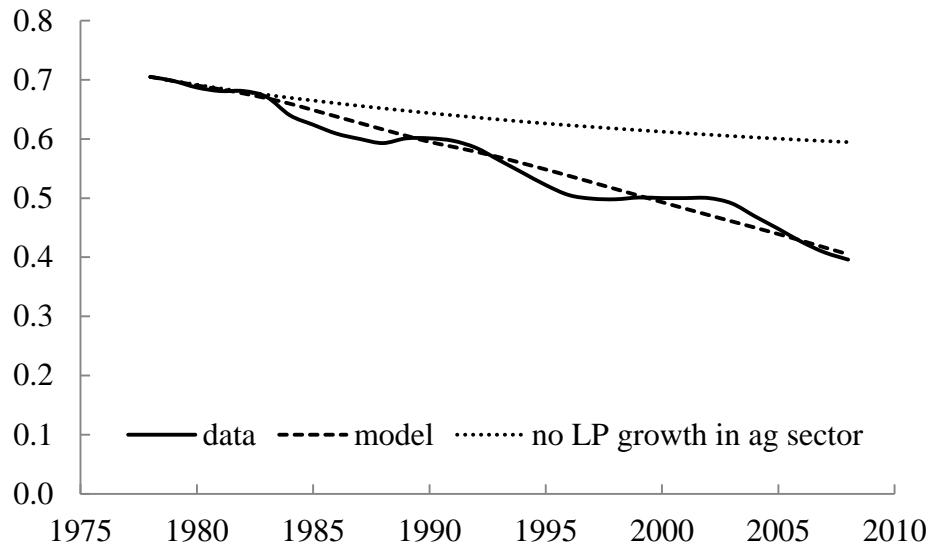
**Figure 5. Agricultural share of employment in China, 1978-2008 (data versus model).**



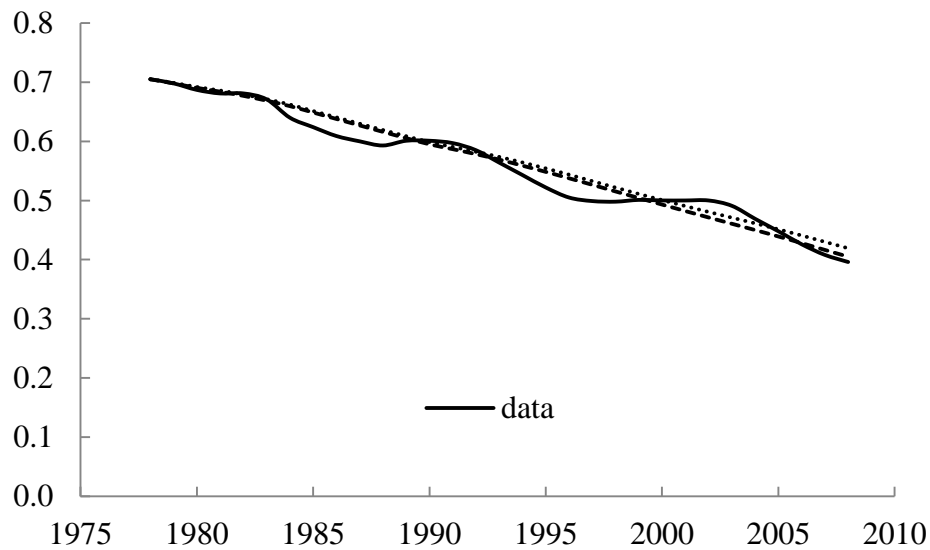
**Figure 6. Agricultural share of employment in China, 1978-2008 (counterfactual exercises: no migration costs).**



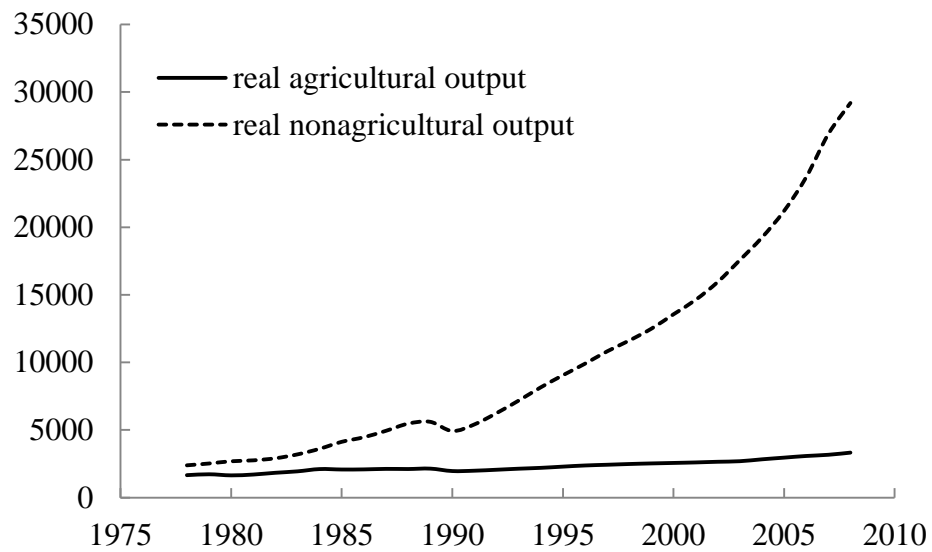
**Figure 7. Agricultural share of employment in China, 1978-2008 (counterfactual exercises: no labor productivity growth in the agricultural sector).**



**Figure 8. Agricultural share of employment in China, 1978-2008 (counterfactual exercises: no labor productivity growth in the nonagricultural sector).**



**Figure 9. Real sectoral output in China, 1978-2008 (constant population).** The real sectoral output with constant population is the product of the real sectoral labor productivity and the sectoral share of employment.



**Table 1. Results of quantitative analysis.**

	Reduction of Agricultural Share of Employment (1978-2008)	Contribution to Structural Transformation
Data	30.9%	
Benchmark model	30.0%	
Counterfactual exercises:		
(1) No the migration costs	40.1%	10.1%
(2) No labor productivity growth in the agricultural sector	11.0%	19.0%
(3) No labor productivity growth in the nonagricultural sector	28.6%	1.4%

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## **Appendix**

The National Bureau of Statistics of China reports the GDP at current prices and the real GDP growth rates. To obtain the real GDP time series for the whole economy and for each sector, this chapter uses the current base year<sup>12</sup> nominal values and compute the economy-wide and sectoral real value-added based upon their real growth rates<sup>13</sup>. Notice that there are two sets of economy-wide real GDP time series, one is the computation based on the real GDP growth rates, the other is the sum of the sectoral real value-added just calculated. However, the difference between them is negligible<sup>14</sup>. In this chapter, the economy-wide real GDP, in particular, refers to the sum of the sectoral real value-added.

### **Sectoral Share of Real GDP**

Each sector's share of the real GDP is its real value-added as percentage of the real GDP.

### **Sectoral Share of Employment**

Each sector's share of employment is its year-end employed persons as percentage of the total employed persons.

### **Sectoral Real Labor Productivity**

Each sector's real labor productivity is its real value-added divided by its year-end employed persons. Notice that the nonagricultural sector is the combination of the secondary industry and the tertiary industry.

### **Sectoral Nominal Labor Productivity**

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<sup>12</sup> According to *China Statistical Yearbook 2009*, the current base year is 2005.

<sup>13</sup> Notice that the sectoral GDP deflators cannot be added up as the aggregate deflator.

<sup>14</sup> This is another proof that 2005 is the base year NBS used to calculate the real growth rates.

Each sector's nominal labor productivity is its nominal value-added divided by its year-end employed persons. Notice that the nonagricultural sector is the combination of the secondary industry and the tertiary industry.

### **III. CHAPTER 2**

#### **TECHNOLOGY DIFFUSION ON THE INTERNATIONAL TRADE NETWORK**

Zhen Zhu, Gary D. Ferrier, and Javier A. Reyes

##### **3.1 Introduction**

Technological progress has long been viewed as a critical engine for sustainable economic growth and poverty reduction. However, since technological innovation occurs almost exclusively in a few high-income countries (Keller, 2004, 2009),<sup>15</sup> the technological progress at a global level largely depends on technology diffusion.<sup>16</sup> The definition of technology diffusion depends on the context of the question. For example, it may refer to the individual selection of new products or techniques at the microeconomic level or to the dissemination of technological information across countries at the macroeconomic level. This chapter adopts the latter perspective since we are interested in the effects of international trade on the diffusion of technologies across countries. Geroski (2000) notes that the principal stylized fact about the diffusion of technology is that it follows an S-shaped curve. The epidemic model of technology diffusion posits that limited information about new technologies restrains the speed of their adoption (Geroski, 2000). In practice, there exist several possible “economic” channels that facilitate the spread of information about new technologies, as well as the technologies themselves, across countries. Among the channels, the two most frequently mentioned are

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<sup>15</sup> Recognizing that technological innovation and adoption of technology are two different phenomena, Nishimizu and Page (1982) propose a decomposition of TFP change into technology change (shifts in the production frontier) and efficiency change or “catching up” (movements toward the production frontier),

<sup>16</sup> The terms “technology diffusion,” “technology transfer,” and “technology adoption” are often used interchangeably in the literature.

international trade and foreign direct investment (FDI).<sup>17</sup> Both trade and FDI help spread knowledge about new technologies through the international flows of goods and services, which provides first-hand knowledge about the existence, uses, and benefits of new technologies. While international trade has received empirical support as an important channel for technology diffusion, the FDI channel has been relatively harder to substantiate because of fewer available data and its obscure mechanism on technology diffusion.<sup>18</sup>

When empirically testing the effects of trade on technology diffusion, the previous literature typically has considered only the direct bilateral trade relationships across countries (Coe and Helpman, 1995, C1H1 hereafter; Keller, 1998; and Comin and Hobijn, 2004, C2H2 hereafter). Unfortunately, empirical results have often been at odds because of the different measurements that have been used to assess trade relationships. For example, C1H1 uses imports to weight foreign R&D expenditures and finds a significant relationship between the weighted foreign R&D expenditures and the domestic total factor productivity (TFP), which can be viewed as the evidence of technology diffusion through trade. Keller (1998) uses the same data as C1H1 but achieves better results by using completely different measures to weight foreign R&D expenditures. Keller (1998) therefore points out that C1H1's results are inconclusive on the importance of trade on technology diffusion and that further work needs to be done.

We conjecture that the impact of trade on technology diffusion would be more accurately measured once we capture both direct and indirect trade relationships by considering the international trade system as a weighted network. The underlying hypothesis is that better-connected countries on the trade network would have higher technology intensities, which

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<sup>17</sup> For more detail, see Hoffman (2013) who notes that there is a large literature across multiple disciplines on the links between technology diffusion and both international trade and FDI.

<sup>18</sup> According to Keller (2004), studies testing the FDI channel have been largely restricted to company-level case studies. Section 3.2 provides some review in this area.

implies more intensive technology diffusion. The network approach would not only consider direct effects that result from the bilateral trade linkages, and their magnitudes, that exist between countries, but also indirect effects that allow countries to access technology information of others where no bilateral trade linkages exist. We can establish an index of proximities among countries so that the connectivity for each country within the network can be measured. Furthermore, higher order degrees of connectivity can be controlled for when using network indicators that can capture indirect network effects. For example, it is possible to analyze the dynamics of technology diffusion by considering core-periphery dynamics in which a number of technologically advanced countries are connected to each other (core), while some countries in the periphery can extract information from the core without having to be connected to all of the technologically advanced countries.

We use annual bilateral trade data from the NBER-United Nations Trade Data (Feenstra et al., 2005) to build a representation of the international trade network, where countries are the nodes of the network and the values of the bilateral trade flows denote the links between them. Furthermore, we merge the international trade network data with the Cross-country Historical Adoption of Technology (CHAT) dataset (Comin and Hobijn, 2009) to study technology diffusion dynamics, where direct and indirect trade linkages on the networks are assumed to be conduits of technology diffusion across countries. The combination of the trade and technology datasets gives us a three-dimension panel with 145 countries and 24 technologies over the 39-year period from 1962 to 2000. Our central finding is that network effects (direct and indirect) can be shown to play significant roles in technology diffusion through trade. In most cases, there is strong and robust evidence to suggest that better-connected countries tend to adopt or assimilate (measured by intensity of use) newer and more advanced technologies faster.

Interestingly, our dataset includes some technologies for which clear substitutes have emerged. For these cases the analysis shows that countries with higher levels of connectivity tend to have much lower levels of adoption of such technologies through time. These two findings together, that newer and more sophisticated (technologically advanced) technologies are adopted or assimilated by better connected countries, while old technologies are disposed of by these same highly connected countries, provide strong evidence of the importance of trade in the process of technology diffusion. Furthermore, the network approach allows us to depict a certain level of efficient technology diffusion phenomena where old, and perhaps obsolete, technologies are displaced by newer ones. These results confirm the assumptions of the quality-ladder models (Aghion and Howitt, 1992) in which old (lower quality) products are continuously replaced by newer (higher quality) products. The network effects consolidate the quality-ladder progression in both adopting new technologies and abandoning old ones.

The remainder of the chapter is organized as follows: Section 3.2 provides a review of the relevant literature. Section 3.3 introduces the trade data and formally defines the trade network. Section 3.3 also describes the technology data and examines the technology diffusion on the trade network. Section 3.4 specifies our empirical methodology and summarizes our major findings. Finally, Section 3.5 provides some discussions and concludes the chapter.

## **3.2 Literature Review**

There is an extensive literature on technology diffusion and there are a number of excellent surveys of this literature. Among others, the most recent are Saggi (2002) and Keller (2004, 2009). Our review of the literature differs from those presented in Saggi (2002) and Keller (2004, 2009) in that we primarily address macro-level studies, with only limited mention

of the growing empirical literature based on micro-level data. Furthermore, the literature review presented here is by no means comprehensive, but rather focuses on the works most germane to our study.

### **3.2.1 Why Is Technology Diffusion Important?**

An important lesson we have learned from empirical studies of economic growth is that the cross-country differences in per capita income can be attributed to the differences in TFP, rather than to the differences in the levels or initial allocations of factors of production (Prescott, 1998; Hall and Jones, 1999; and Restuccia et al., 2008).<sup>19</sup> TFP, also known as the Solow Residual, is a “black box,” which can be interpreted as technological, institutional, and cultural factors or any other factors besides labor and (physical and human) capital inputs that influence productivity. Since most of these other factors are unobservable, it is difficult for economists to quantify each factor’s contribution to TFP. However, most economists would agree that technology plays a key role in determining TFP.

According to Keller (2004, 2009), for most countries, foreign sources of technology are estimated to account for 90% or more of domestic productivity growth. Although the contribution of India, China, and a number of other countries is rising, most of the world’s technology creation has occurred almost exclusively in a few rich countries. The pattern of worldwide technological change is thus determined in large part by international technology diffusion.

Keller (2004, 2009) further points out, that international technology diffusion, through its effects on TFP, affects both the distribution and the growth of world incomes. First, whether

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<sup>19</sup> The opposite stand is that cross-country differences are due to differences in capital per worker, where capital includes both physical and human capital. One of the most influential examples would be Mankiw et al. (1992).

countries' incomes converge over time depends on whether technology diffusion is global or local. A better understanding of technology diffusion therefore provides insights into the likelihood that certain less developed countries will catch up with rich ones. Second, strong cross-country technology diffusion will generally raise the rate at which the world's technology frontier advances. Thus, it is impossible to overstate the importance that the dynamics of technology diffusion have in the context of global economic growth and poverty reduction.

### **3.2.2 Technology Diffusion in Theory**

Theoretically, links can be established among technology, diffusion channels (primarily trade and FDI) for technology, and economic growth. Centering on technology diffusion, one strand of the literature investigates the pairing of technology diffusion and economic growth, while another strand examines the pairing of technology diffusion and diffusion channels, and still another strand combines these two (Eaton and Kortum, 2001). Here, we begin by discussing the studies focusing on the first relationship considered—technology diffusion and economic growth.

Who is the beneficiary of technological progress? Is it the case that, immediately after invention, technology becomes available everywhere and each country enjoys the same level of technology (Solow, 1956; Mankiw et al., 1992)? Or is it the case that, each country can only promote its productivity by its own innovation (Romer, 1990; Aghion and Howitt, 1992)? Eaton and Kortum (1999) argue that the reality would fall somewhere between these two extremes and that global productivity growth is gradually driven by innovation from a small set of countries.

It is well known in economics that technology is a non-rival good: it can be used simultaneously by multiple agents (Romer, 1990). However, as Saggi (2002) points out, non-rivalry does not mean that technology can be transferred across agents at zero cost. The non-rival



nature of technology only implies that if two agents are willing to pay the cost of adopting a new technology and have access to it, they can adopt it without interfering with each other's decisions. Therefore, given the access to new advanced technologies, diffusion takes place only if the benefit of innovation is greater than the cost of adopting technology from abroad.

A natural starting point for studying technology diffusion is to modify the standard neoclassical growth model by assuming that there is access to new technology and introducing the cost of adopting it. Parente and Prescott (1994) emphasize barriers to technology adoption as a key determinant of differences in per capita income across countries. In their model, although any firm can access the underlying stock of knowledge in the world economy, the cost of such access differs across countries due to differences in legal, regulatory, political, and social factors. Thus in their view, some countries make it inherently costlier for their firms to adopt new technologies and thereby retard the development of the entire economy.

An obvious drawback of Parente and Prescott's (1994) approach and of the neoclassical growth model in general, is that technological change itself remains unexplained. Without a solid explanation of technological change, it is difficult to explain the diffusion of technology. For this reason, the endogenous growth model has become attractive. Two widely used strands of endogenous growth theory are the models of expanding varieties (Romer, 1990) and the models of quality ladders (Aghion and Howitt, 1992). The former captures the horizontal innovation process, while the latter captures the vertical innovation process. Therefore, the key difference between these two strands is that in the varieties model new products do not make old ones obsolete, while in the quality ladders model new products will replace older ones. In studying technology diffusion and growth, examples based on the quality ladders model are Eaton and Kortum (1996) and Howitt (2000) and an example based on the varieties model is Barro and

Sala-i-Martin (2004). Barro and Sala-i-Martin (2004) note that similar results could be obtained from either the varieties or quality ladders models. The main idea is that follower countries tend to catch up with the leaders once imitation and implementation of discoveries are cheaper than innovation. Klenow and Rodriguez-Clare (2005) stress two features shared by both types of models. The first is that, in steady state, all countries grow at the same rate due to technology diffusion. The second feature is that the differences in policies or other country parameters (e.g., diffusion barriers) generate the differences in TFP levels rather than in growth rates.

Now we turn to the studies on the relationship between technology diffusion and diffusion channels. The primary channels for technology diffusion are international trade and FDI, by which knowledge is transferred in both embodied and disembodied forms (Helpman, 1997). Traditional theories of trade often assume that technological change is exogenous and that trade stems from comparative-advantage-based specialization, where comparative advantage is determined by locally available technology. In contrast, dynamic relations and endogenous technical change have been incorporated in recent studies. That is, not only can technology affect the trade patterns, but international trade and FDI can result in differences in technology by serving as channels for diffusion (Grossman and Helpman, 1995). As noted in Helpman (1997), trade and FDI contribute to technological progress by making available products and services that embody foreign knowledge, and by providing foreign technologies and other types of knowledge that would otherwise be unavailable or very costly to acquire.

### **3.2.3 Technology Diffusion in Practice**

In practice, concepts such as technology and technology diffusion need to be pinned down by observable proxies. As documented in Keller (2004, 2009), three widely used indirect means to measure technology are (1) inputs (R&D), (2) outputs (patents), and (3) the effect of

technology (higher productivity). Two measures of international technology diffusion are (1) market transactions and (2) externalities. Market transactions refer to royalty payments for the use of patents, licenses, and copyrights. Although data on market transactions is available for most industrial economies, many economists believe that most international technology diffusion occurs not through market transactions but rather through externalities (spillovers), where international trade and FDI, among other factors, serve as conduits.

An empirical benchmark is to test the hypothesis that technology diffusion is shaped by geography (Keller, 2009). One interpretation of the hypothesis is that technology diffusion within countries is stronger than across countries. Another interpretation is that technology diffusion weakens as distance increases. The evidence generally supports these hypotheses. For example, Eaton and Kortum (1999) find that for the G-5 countries (France, Germany, Japan, the UK, and the US), the rate of domestic technology diffusion is much higher than the typical rate of international technology diffusion across these countries. Keller (2002) finds a negative relationship between distance and the strength of technology diffusion—with each additional 1,200 kilometers distance there is a 50% drop of technology diffusion.

The benchmark approach tells us that geography matters. However, the estimated geographic effects may be due to unobserved heterogeneity across locations. To take into account the heterogeneous factors, we review some empirical studies focusing on specific diffusion channels in the remainder of this section.

One of the most frequently mentioned channels of technology diffusion is international trade. International trade can be further divided into the roles played by exports and imports.<sup>20</sup>

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<sup>20</sup> Theoretically speaking, technology may be diffused through both importing and exporting. Empirical evidence strongly supports the importing channel, while the exporting channel is relatively harder to justify. See Keller (2004, 2009) for detailed survey.

With respect to exports, case studies of the export success of a number of East Asian countries starting in the 1960s are particularly strong in their emphasis on the learning-by-exporting effects (Rhee et al., 1984). Based on a non-parametric dynamic model of productivity, Ferrier et al. (1998) find that Yugoslav co-operatives that adopted an export orientation performed better than those that did not. A more recent econometric treatment of learning-by-exporting is De Loecker (2010). Using firm-level data, he finds substantial additional productivity gains from entering export markets. As for imports, the seminal paper C1H1 finds positive and significant effects of import-share-weighted foreign R&D stock on domestic TFP for a group of OECD countries. However, as is the case with many pioneering works, C1H1 continues to be challenged. For instance, Keller (1998) is skeptical about their results. He uses randomly assigned import shares to construct foreign R&D stock and obtains better results than C1H1. Furthermore, instead of using overall trade as in C1H1, Xu and Wang (1999) find that technology diffusion is specifically associated with the trade of differentiated capital goods. Xu and Wang (2000) examined the effects of both trade and FDI on technology diffusion. They find that trade in capital goods is associated with diffusion of technology and that outward FDI is associated with technology diffusion but that inward FDI is not.

Second, recent studies have shown great interest in FDI as a channel of technology diffusion. A number of case studies have been conducted based on particular multinational enterprises. For example, a case study of Intel's FDI into Costa Rica provides us with interesting information that a major high-tech company can trigger enormous technological change in a relatively small country (Larrain et al., 2000). Also, the temperature controlled supply chain operations that Walmex, Wal-Mart's affiliate in Mexico, introduced in the 1990s were soon copied by all of Walmex's retail competitors (Iacovone et al., 2009). To draw more general

implications, instead of doing a case study, Xu (2000) uses the Bureau of Economic Analysis data on US outward FDI into 40 countries over almost 30 years and finds generally a positive relation between FDI and domestic productivity growth, which is stronger in the developed countries than in the less developed ones.

### **3.2.4 Network Effects on Technology Diffusion**

The current chapter is an empirical study on trade's effects on technology diffusion. In this regard, it belongs to the literature pioneered by C1H1. Before we go to our contributions, it is worth noting two major drawbacks of C1H1. One is that they only consider direct bilateral trade. However, technology may also flow through indirect trade relationships. The other is a potential endogeneity problem associated with their model specification, an issue that will be discussed in more detail below.

Suppose that there are only three countries in the world, countries A, B, and C. Suppose that A only trades with B, while B trades with both A and C (see Figure 1). Based on C1H1's model, there can be no technology spillover between A and C because of the absence of direct bilateral trade between them. However, B may serve as an intermediary between A and C so that A indirectly "trades" with C and thus technology may diffuse from A to C. These indirect effects emerge as B adopts technology from A and then trades with C, which in turn can lead to C adopting technology that originally emerged from or is diffused primarily by A.

Recent literature has given attention to the indirect trade effects. For example, Lumenganeso et al. (2005) find that the indirect trade effects on domestic TFP are at least as important as the direct bilateral trade effects. Moreover, Franco et al. (2011) translate the indirect trade effects into the "economic distance" among countries and find that they play a significant role in determining domestic TFP. Although these studies also focus on the indirect effects, there are at

least two differences vis-à-vis our study. First, the above studies are based on recalculating the weighted foreign R&D stock, while ours is based on an explicit network indicator to capture the interconnectedness between countries. Second, as explained more fully later in this section, we use specific technologies rather than TFP as the dependent variable which mitigates the endogeneity problem that the above studies might suffer.

[Insert Figure 1 here]

Network analysis is well suited to identify the indirect trade effects. Briefly speaking, a network is a description of the pattern of connections between a collection of nodes (or vertices) and links (or edges) (Watts, 2003; Newman, 2010). Many natural or social phenomena can be represented by networks. For example, one of the most studied networks is the Internet, where the nodes are the computers and the links are the (wired or wireless) connections between them. Networks often vary from one another due to differences in their structures. However, a number of indicators or algorithms can be utilized to study the network structure, such as shortest paths, centrality, and clustering coefficients (Newman, 2010). As a powerful methodological tool to study the interconnectedness between nodes (or vertices), network analysis has been widely applied in a diverse set of disciplines such as information technology, biology, and sociology (Watts, 2003; Newman, 2010). Within the economics literature, network analysis has received rapidly increasing attention and has been used to explain economic development, economic integration, and financial contagion (Reyes et al., 2008; Kali and Reyes, 2010; Schiavo et al., 2010) at the macro level, and market externalities (Shapiro and Varian, 1998; Goyal, 2007) at the micro level, among other phenomena.

The international trade system can be considered an interdependent, complex network, with countries serving as nodes and trade relationships serving as links. Network effects take into account both the direct and indirect relationships between any two nodes. Specifically, the network effects can be represented by a number of network indicators that measure the distance between nodes. As mentioned above, previous studies have considered the role that geographical distance plays in technology diffusion. Likewise, by constructing network indicators, we can test the effects of network distance (i.e., the inverse of network proximity) on technology diffusion. Importantly, while geographical distance is fixed over time,<sup>21</sup> network distance displays rich dynamics over the period we examine. Thus, network analysis provides us with a novel and important tool for exploring the diffusion of technology. One prominent indicator of the network effects is the geodesic distance (or simply, distance). It measures the shortest path between nodes, which is not necessarily the direct bilateral paths between them. In this chapter, we hypothesize that trade is the major channel for technology diffusion across countries and examine the technology diffusion on the international trade network. In particular, using the shortest paths algorithm, we calculate the average distance to measure how well each country is connected in the trade network. We find that the average distance has a significant impact on technology diffusion<sup>22</sup>.

As noted above, a potential problem of C1H1 is the endogeneity of their econometric model. They specify domestic TFP as the dependent variable to represent the outcome measure of technology, while using domestic and foreign R&D stocks as independent variables to

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<sup>21</sup> A fairly recent study by Comin, et al. (2012) falls into this category. They assume that countries can learn faster if they are closer to each other in geographical sense.

<sup>22</sup> Actually, what we find is the significant impact of the average distance on country's technology intensity level. The implicit assumption here is that technology intensity is mainly the result of technology diffusion.

represent the input measures of technology. However, the causal effects, if any, could go from dependent variable to independent variables as well. That is, a country with higher productivity, will likely engage in more R&D activities. One way to address the endogeneity problem is to use direct measure of technologies. C2H2 pioneer the use of historical technology adoption data. They have compiled the Cross-country Historical Adoption of Technology (CHAT) dataset (Comin and Hobijn, 2009), which contains intensity measures of 104 technologies across numerous countries. For specific types of technologies, they find that trade openness, human capital, and institutions are important determinants of the speed of technology adoption. The issue of endogeneity is alleviated because it is reasonable to believe that any specific technology as dependent variable should not reversely affect the aggregate control variables such as GDP, trade openness, and human capital.

This chapter thus addresses the two drawbacks of C1H1 and uses a novel empirical approach that expands on the efforts of C2H2. First, we look at specific industries and technologies and examine the technology adoption process by utilizing the CHAT dataset. Second, we take into consideration the network effects and compute the average distance to capture indirect trade-related technology diffusion. We find that trade network effects, as captured by the average distance, play a significant role in technology diffusion. Our results support the argument that the better connected countries benefit more from trade-induced technology diffusion as observed by higher levels of technology intensity. Additionally, the results presented here can also be interpreted as evidence for the quality-ladder phenomena described in the economic growth literature (Aghion and Howitt, 1992).

### **3.3 Trade Network and Technology Data**



The international trade system can be viewed as an interdependent, complex network through which technology can be diffused or knowledge can be transferred. Countries serve as nodes and their bilateral trade relationships act as the links between them. We use the bilateral trade flows reported in the NBER-United Nations Trade Data (Feenstra et al., 2005) to construct the trade network. The database covers the years 1962-2000 and 203 countries and areas. The data are organized in an  $N \times N$  bilateral trade matrix  $B$  for each year, where  $N = 203$ , each cell  $b_{i,j}$  represents the trade flows from country  $j$  to country  $i$ , with  $b_{i,i} = 0$ .

Arguably, data reported by importing countries is more reliable than the data reported by exporting countries.<sup>23</sup> We use the imports reported by countries to build the bilateral trade flows, where the imports of country  $i$  from country  $j$  correspond to the exports of country  $j$  to  $i$ .<sup>24</sup> In this chapter, we use a total trade approach and compute the total trade (symmetric) matrix  $W = B + B'$ , where  $w_{i,j} = b_{i,j} + b_{j,i} = w_{j,i}$ .

The objective of this chapter is to utilize the international trade network as the conduit through which technology diffuses internationally. The assumption is that technological knowledge and know-how are somehow embedded in exports/imports. To test the hypothesis that countries that are better connected or are closer (in terms of network proximity) to the innovation hubs or to early technology adopters will tend to adopt new technologies at a faster

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<sup>23</sup> This is, in part, because tariffs are often collected on imports.

<sup>24</sup> Regarding the historical unification or fragmentation, we always consider the geographically larger economy as the only predecessor or the only successor so that the methodology is consistent with the technology data. For example, we consider Russia as the only successor of Former USSR and all other Former USSR countries as completely new countries after 1991. Also, since the former Federal Republic of Germany is geographically larger than the former German Democratic Republic, we consider Former Federal Republic of Germany as the only predecessor of Germany before 1991. See Table 1 for information on how we merge the trade data.

rate, we need to be able to quantify technology adoption or the intensity of the utilization of various technologies.

To study the dynamics of technology diffusion through the international trade network, we use the Cross-country Historical Adoption of Technology (CHAT) dataset that has information of 104 technologies for more than 150 countries since 1800. To make cross-country comparisons meaningful, we need to convert the original technology measures in the CHAT dataset into the intensity measures. Except for three generally used technologies—computers, electricity production, and internet users—the CHAT dataset divides the 104 technologies into 8 industries: agriculture, finance, health, steel, telecommunications, textiles, tourism, and transportation. This chapter excludes the agriculture, finance, and tourism industries because the sizes and natures of these industries differ substantially across countries and the appropriate intensity measures of technologies in these industries are difficult to define.

In this study we follow the strategy of C2H2 and compute the following types of intensity measures for the different industries considered: 1) percentages of population for the health industry, e.g., percent of children aged 12-23 months who received a DPT immunization before the age of one year; 2) production shares for the steel, textiles, and transportation industries, e.g., fraction of the total crude steel produced in blast oxygen furnaces; 3) volume/amount per unit of real GDP measures for the steel and transportation industries, e.g., the aviation cargo (ton-kilometers) per unit of real GDP; 4) per capita measures for the telecommunications and transportation industries, e.g., televisions per capita. Table 2 contains descriptions of the 24 technology intensity variables used in this chapter.

[Insert Table 2 here]

After combining the international trade network and the technology datasets, our sample period is restricted to 1962-2000 and the number of countries included in the analysis is 145. Before we can use the data for the study of technology diffusion dynamics through the international trade network, we need to articulate the network connectivity measure that we can use to capture the direct and indirect effects of trade.

As mentioned in the introduction, we are interested in exploring the degree of connectivity to the innovation hubs, i.e., early adopters of new technologies, by focusing on a concept of network proximity. The information about linkages and nodes embedded in the network representation of the international trade system can be utilized to define the network proximity. Previous network studies have characterized the distance between nodes by the strength of the linkages between them. The values of bilateral linkages between two countries,  $w_{i,j}$ , can be interpreted as a measure of their degree of connectivity or proximity. Larger bilateral trade flows lead to stronger relationships and higher rates of proximity. In other words, the strength of bilateral trade flows provides a measure of proximity from a first order degree perspective. Higher order network proximity can be computed as well if one considers indirect paths from one node to another. Figure 2 can be used to visualize the possible direct and indirect paths that can be followed to link countries (i.e., network nodes) A and C. Ignoring the values for the links and just concentrating on the presence of links between nodes, one could go directly from node A to C via the direct link between the two nodes, or one could go through node B (indirect path) to connect A and C. If one is interested in the distance between two given nodes, one should consider both alternatives—direct (bilateral) and indirect links—and determine which path is shorter. In a weighted network, such as the international trade network considered here,

the path between countries is determined by the strength of their total trade linkages. Higher bilateral trade flows denote shorter paths and thus higher rates of proximity. The higher the trade volume is between countries  $i$  and  $j$ , the closer (or the higher the rates of proximity) these countries are to each other. In other words, one can use the reciprocal of the trade volumes to determine a sense of proximity between countries.

[Insert Figure 2 here]

It is important to be able to capture not only the distance to the technology hubs based on trade, but also to capture the ability of a given country or set of countries present in the shortest path between countries  $i$  and  $j$  to diffuse/transfer technology. For any particular country in the network, technology intensity levels in connected foreign countries matter in the technology diffusion process. That is, the higher is the technology intensity level in a given country, the more technological knowledge this country is expected to diffuse through its trade linkages. Therefore, higher foreign technology intensity level also means shorter distance. In sum, when we calculate the shortest paths for each particular country, we consider not only the trade volume but also the foreign technology intensity level.

Let  $t_i$  denote the technology intensity of country  $i$ . As noted above,  $w_{i,j}$  denotes the bilateral total trade volume between countries  $i$  and  $j$ . We can define a proximity matrix,  $P$ , where each element  $p_{i,j}$  is the bilateral path from country  $j$  to country  $i$ , where  $p_{i,j}$  is calculated as:

$$p_{i,j} = \frac{1}{t_j w_{i,j}} \quad (1)$$

Notice that the proximity matrix  $P$  is asymmetric because  $p_{i,j}$  does not have to equal  $p_{j,i}$ . Equation (1) gives us a distance (or proximity) measure for the technology diffusion network. Bigger  $t_j w_{i,j}$  indicates higher rates of proximity (i.e., shorter bilateral paths) for country  $i$  so that more technology is expected to diffuse towards country  $i$ . However,  $p_{i,j}$  only captures bilateral distance. Technology may also be diffused through intermediate countries—for example, if countries A, B, and C are trading with one another (see Figure 3).<sup>25</sup> The bilateral path from C to A is  $p_{AC}$ , while the indirect path from C to A is  $p'_{AC} = p_{AB} + p_{BC}$  with country B serving as an intermediary between A and C. Note that the indirect path  $p'_{AC}$  between countries A and C may be shorter than the direct path  $p_{AC}$  between them.

[Insert Figure 3 here]

For country  $i$ , the shortest of all direct (bilateral) and indirect paths from country  $j$  to country  $i$  is denoted as the shortest path  $s_{i,j}$ .<sup>26</sup> Finally, the average distance to all  $n$  technology-available trading partners from country  $i$  is thus defined as:

$$d_i = \frac{\sum_{j=1}^n s_{i,j}}{n} \quad (2)$$

C2H2 take into account the foreign impact on technology intensity level in the home country by using the trade-share-weighted average of technology intensity levels of trading

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<sup>25</sup> Notice that the link between countries is directed. For example, when we calculate the shortest path for country A, only the paths directed to A will be counted. In other words,  $p_{AB} + p_{CB}$  is not a plausible alternate path for country A because the two paths have conflicting directions.

<sup>26</sup> We solve the shortest path problem by using the Floyd-Warshall algorithm.

partners as a control variable. However, the trade shares they use are based only on bilateral trade. Hence, the network effects are ignored in C2H2. In C2H2's specification, the trade-share-weighted foreign technology level for country  $i$  is denoted as  $tw_i$  and is calculated as the following:

$$tw_i = \frac{\sum_{j=1}^m t_j w_{i,j}}{\sum_{j=1}^m w_{i,j}} \quad (3)$$

where  $m$  is the number of countries with which country  $i$  has bilateral trade relationships. We reserve this measurement as another control variable in our econometric specification below. Our primary objective is to test the significance of the network distance  $d$  on technology diffusion while controlling for other important variables such as  $tw$  so that our results can be directly compared with those from the extant literature.

Before we proceed to the econometric modeling and results it is worthwhile to briefly describe the technology data. First, we look at the cross-country average technology level over time (see Figure 4). The main finding here is that most technologies have displayed an upward trend over time, which means that the adoption level has been increasing globally. However, “Steel\_OHF,” “Mail,” “Telegram,” “Textile\_artificial,” and “Railway\_cargo” have shown clear patterns of decline in recent years, while “CableTV,” “Newspaper,” and “Railway\_passenger” have been roughly constant in recent times. Another way to determine whether the technology has become obsolete is to examine the fitted kernel density distribution function for selected years. To illustrate this idea, we pick “Cellphone” as a typical new technology and “Telegram” as a typical obsolete technology. In the top panel of Figure 5 we show the kernel functions for log measures of “Cellphone” and “Telegram.” Clearly, the mode of “Cellphone” has moved to

the right along the horizontal axis, which confirms that “Cellphone” is a relatively new technology that has gained popularity over time. In stark contrast, the distribution of “Telegram” has shifted leftward over time, which confirms that it has become an obsolete technology. As shown in the bottom panel of Figure 5, the same conclusions can be drawn if we compare the two technologies in terms of growth rate distributions.

[Insert Figure 5 here]

### 3.4 Empirical Model and Results

The previous literature basically follows two strands to test the trade effects on technology diffusion. The first strand follows C1H1, where the technology adoption level is indirectly measured by TFP. In C1H1’s specification, the dependent variable is TFP, i.e.,  $\frac{Real\ GDP}{K^{1-\alpha}L^\alpha}$ , where  $K$  is capital and  $L$  is labor. The independent variables include domestic R&D stocks, measured by domestic R&D expenditure, and foreign R&D stocks, measured by foreign R&D expenditures weighted by import shares. As mentioned earlier, endogeneity may be a problem with this specification because TFP may in turn affect domestic R&D expenditure.

Another strand is to use direct measures of technology diffusion, which follows C2H2. Their study uses the Historical Cross-Country Technology Adoption Dataset (HCCTAD) and considers more than 20 major technologies across 23 advanced countries over more than 200 years. Instead of using indirect measure of technology like TFP, they use direct technology intensity measure as the dependent variable. Furthermore, their control variables typically include a number of potential determinants of technology adoption, which can be classified into 5 groups: (1) real GDP per capita, (2) human capital endowments, (3) trade variables that include

openness and measures of the level of development of a country's trading partners, (4) institutional variables, and (5) technology interaction terms. As mentioned in Section 3.2, given the rich datasets of specific technologies, they are able to ameliorate the endogeneity problem facing C1H1.

Our baseline specification is a country-fixed-effects model, which can be seen as an extension of C2H2. In Equation (4), the dependent variable is the intensity level  $Y_{it}^k$  for technology  $k$  in country  $i$  for year  $t$ . The country-specific fixed effects  $C_i$  are controlled for and capture the country-specific characteristics such as geographical and institutional factors that might affect the technology adoption level but remain constant over time. We include a network effects indicator, the average distance, as an independent variable and denote it as  $D_{it}$ . Other control variables include  $RGDP_{it}$  as real GDP per capita, and  $Openness_{it}$  as openness, which is the ratio of nominal trade volume to nominal GDP<sup>27</sup>. Like C2H2, we also calculate the trade-share-weighted average of technology intensity levels of trading partners and denote it as  $TW_{it}^k$ . The model is thus:<sup>28</sup>

$$Y_{it}^k = \sum \beta_{1i}C_i + \beta_2 D_{it}^k + \beta_3 RGDP_{it} + \beta_4 Openness_{it} + \beta_5 TW_{it}^k + \epsilon_{it}^k \quad (4)$$

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<sup>27</sup>  $RGDP$  is calculated based on the CHAT dataset.  $Openness$  is extracted from the Penn World Table 7.0 (Heston et al., 2011). Other possible control variables include the primary school enrollment and the secondary school enrollment rates. Unfortunately, data on school enrollment is not available in many cases. Therefore, to ensure a large number of observations, and to avoid problems of multicollinearity, we don't include the education (human capital) variables in the regression models reported in the body of the text. Regression results for models with education variables are reported in Tables A1a and A1b in the Appendix; qualitatively, the results don't differ across the two specifications.

<sup>28</sup> Note that some technology intensities are measured as percentages. In these cases, we don't transform  $Y_{it}$  into logarithmic scale. For the same reason,  $Openness$  is also unlogged.



We run the above specification for each of the 24 technologies we examine. This allows for different estimated coefficients for the different technologies since the nature of each technology can be different thus allowing the control variables we consider to have different impacts.

The coefficient of primary interest is  $\beta_2$ , which measures the impact of the average distance on the level of technology adoption. If the better connectedness on the trade network is beneficial for the technology diffusion process, we should observe that  $Y$  and  $D$  are negatively correlated. That is, the smaller is  $D$ , meaning the closer to the trading partners, the more technology diffusion tends to occur.

Tables 3a and 3b report the country-fixed-effects regressions results. Because serial correlation, which would lead to biased and less efficient estimates, is a possibility we use Wooldridge's test to examine whether serial correlation is present in our panel data model (Wooldridge, 2002; Drukker, 2003). Indeed, we find that serial correlation is present for most of our technology specific regressions.<sup>29</sup> As a result, we use Arellano's (1987) robust estimator to calculate standard errors that are valid in the presence of serial correlation or heteroskedasticity.

[Insert Table 3 here]

Our central findings can be summarized as follows:

1) For both the first-differenced model and the fixed-effects model, after controlling the independent variables such as *RGDP*, *Openness*, and *TW*, we find significant results for the distance variable  $D$ . Recall that if  $D$  is negatively correlated with technology intensity level, we

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<sup>29</sup> Except for "Autoloom," the null hypothesis of no first-order serial correlation is rejected at 1% level for all of the technologies we consider.

should observe significant negative sign for  $\beta_2$  in equation (4). This is indeed the case for most technologies. As the country becomes closer to the trading partners with the technology, it tends to have higher technology intensity level. This pattern is well supported in the health industry, for both types of immunization have negative signs on  $D$ . This is also true for relatively newer technologies, such as “Steel\_EAF” in steel industry, “TV” in telecommunication industry, “Textile\_synthetic” in textile industry, and “Aviation\_passenger” and “Car” in transportation industry. Furthermore,  $D$  is significantly negative for general technologies like “Electricity” and “Internet.”

2) Obsolete technologies, or the old technologies for which clear substitutes have emerged, have either positive signs or insignificant coefficients on  $D$ . These include “CableTV,” “Mail,” and “Telegram” in the telecommunications industry, “Textile\_artificial” in the textiles industry, and “Railway\_passenger” and “Railway\_cargo” in the transportation industry. This is not surprising because for obsolete technologies the better connected countries on the trade network tend to specialize away from them.

Taken together, these two findings that the better connected countries tend to perform better in both adopting relatively newer technologies and in casting away the old or perhaps obsolete technologies for which clear substitutes have emerged, can be viewed as strong evidence of the importance of trade in the process of technology diffusion. Furthermore, the network approach allows us to depict a certain level of efficient technology diffusion phenomena where old technologies are displaced by newer ones. These results confirm the assumptions of the quality ladders models (Aghion and Howitt, 1992) in which old (lower quality) products are constantly being replaced by new (higher quality) products. The network effects consolidate the quality ladder progression in both adopting new technologies and abandoning old ones.

As a robustness check, we have run the pooled OLS regressions for each technology. The central results on the key variable  $D$  are unchanged. However, other control variables become a lot more significant in the OLS model relative to the fixed-effects model. This is indeed what we expected, since in the fixed-effects model the country-specific characteristics have taken away the impact from development factors like national income and education. That is, the development factors are highly correlated with the country's characteristics, i.e., fixed effects over time. The details of the pooled OLS results are as follows:

First, the pooled OLS results show that most types of technologies have expected positive signs and significances for  $RGDP$  and  $Openness$ , meaning that the bigger the economy is and the more open the economy is, the higher technology adoption level will be. This is also largely true with the education variables  $Primary$  and  $Secondary$  (if included). As the country has more human capital, it is more likely to absorb new knowledge and technology for the rest of the world. One interesting exception to the above conclusion is the steel industry, where  $RGDP$  is significantly negative for “Steel\_EAF” and “Steel\_OHF” and  $Primary$  is significantly negative for “Steel\_BOF” and “Steel\_EAF.” It seems that as a country develops higher human capital and income levels, it tends to specialize away from the steel industry, which is considered a preliminary manufacturing industry. It is worth noting that  $Openness$  also has significant negative sign for “Steel\_OHF.” However, as shown in Figure 3, “Steel\_OHF” is an obsolete technology. So becoming more open to the rest of the world will help country to eliminate “Steel\_OHF” and replace it with more the advanced steel production methods “Steel\_BOF” and “Steel\_EAF.” Another interesting exception is railroad transportation, where  $Openness$  is significantly negative for “Railway\_passenger” and “Railway\_cargo.” One interpretation is that

countries switch to other transportation means such as sailing and aviation once it becomes more open to the rest of the world.

Coinciding with the results in the previous literature, the traditional variable controlling for trade effects, the trade-share-weighted average of technology intensity levels of trading partners, has the expected signs and significances for most technologies in the pooled OLS regressions. Specifically,  $TW$  is significantly positive for most technologies, meaning that the bilateral trade weighted foreign technology level is positively correlated with domestic technology adoption level. In other words, the more technology the country's trading partners have (weighted by bilateral trade volume), the more technology it will have domestically. Some interesting exceptions occur in the older technologies "Mail" and "Railway\_cargo," where  $TW$  is significantly negative.

Finally, to see the potentially different technology diffusion patterns between "innovator" countries and "imitator" countries, we also run the country-fixed-effects and the country-random-effects models with a dummy variable  $G7$ , which stands for the Group-7 countries (US, UK, Japan, Germany, Canada, France, and Italy) which are the most innovating countries in the world.<sup>30</sup> In particular, the fixed effects model adds an interaction term  $G7*D$  and the random effects model includes both an intercept term  $G7$  and an interaction term  $G7*D$ .

The major result is that  $G7*D$  does not matter for most technologies. However, when it does matter, it is significantly positive and offsets the negative impact from  $D$  (except for the steel industry). That is, compared with the "imitators," the "innovators" tend to have higher technology intensity level if they are farther away from the rest of the world on the trade network.

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<sup>30</sup> In recent years, the contribution to global innovation from other advanced economies or even developing countries such as China and India has increased rapidly. However, since our sample is restricted within 1962-2000, the G7 is still a fairly informative representation of the world technological frontier back to that time.

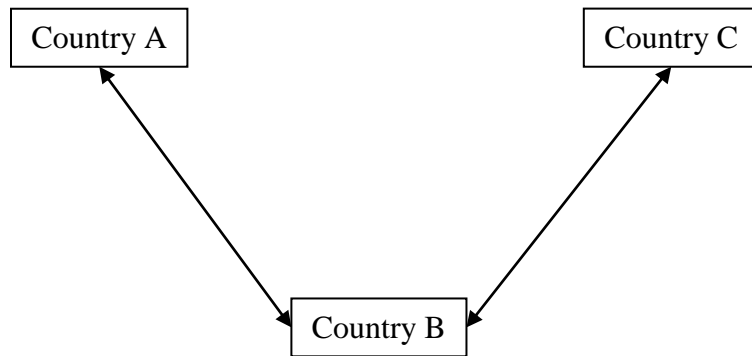
This makes sense for two reasons. First, this can be interpreted as “lock” or “protection” effects from the “innovators.” Since the “innovators” have strong incentives to protect their advanced technologies from the “imitators” until enough economic benefits have been extracted, they tend to develop and intensify those technologies for which they are farther away from the “imitators.” Second, it means that “imitators” can benefit more from the better connectedness on the trade network, which also fits our intuition.

### **3.5 Concluding Remarks**

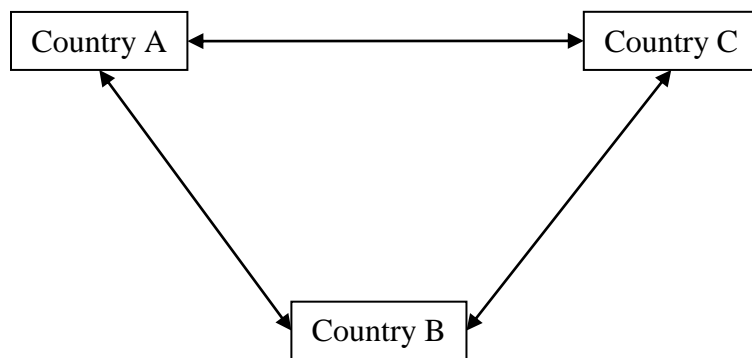
Theoretically, trade serves as a major channel of technology diffusion. To empirically test the effects of trade on technology diffusion, previous literature typically considers the direct bilateral trade effects on the indirect measures of technologies (TFP). We conjecture that the impact of trade on technology diffusion would be more accurately measured once we take into account the indirect network effects and use the direct measures of technologies (intensity level). The international trade system can be considered as a weighted network, upon which technology may be diffused, not only bilaterally between two countries, but also through the network effects, i.e., indirectly by trading with the intermediate country. Specifically, we take into consideration the network effects by calculating a network effects indicator, the average distance (the inverse of network proximity). We find that the network effects play a significant role in technology diffusion through trade. That is, the better connected (measured by the network distance) countries tend to perform better in both adopting relatively newer technologies and in casting away the old or perhaps obsolete technologies for which clear substitutes have emerged. These results confirm the assumptions of the quality-ladder models (Aghion and Howitt, 1992) in

which old (lower quality) products are constantly being replaced by new (higher quality) products.

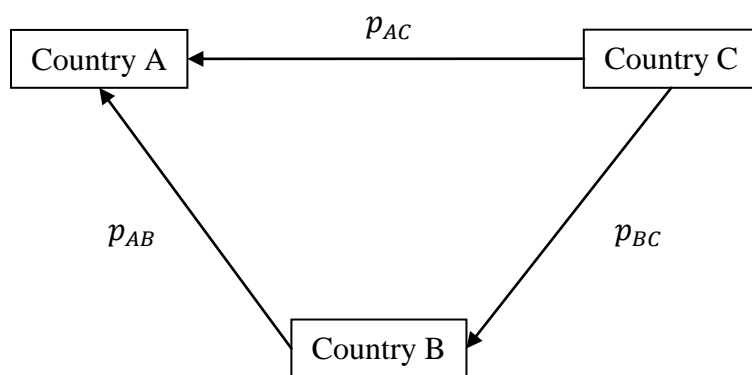
**Figure 1.**



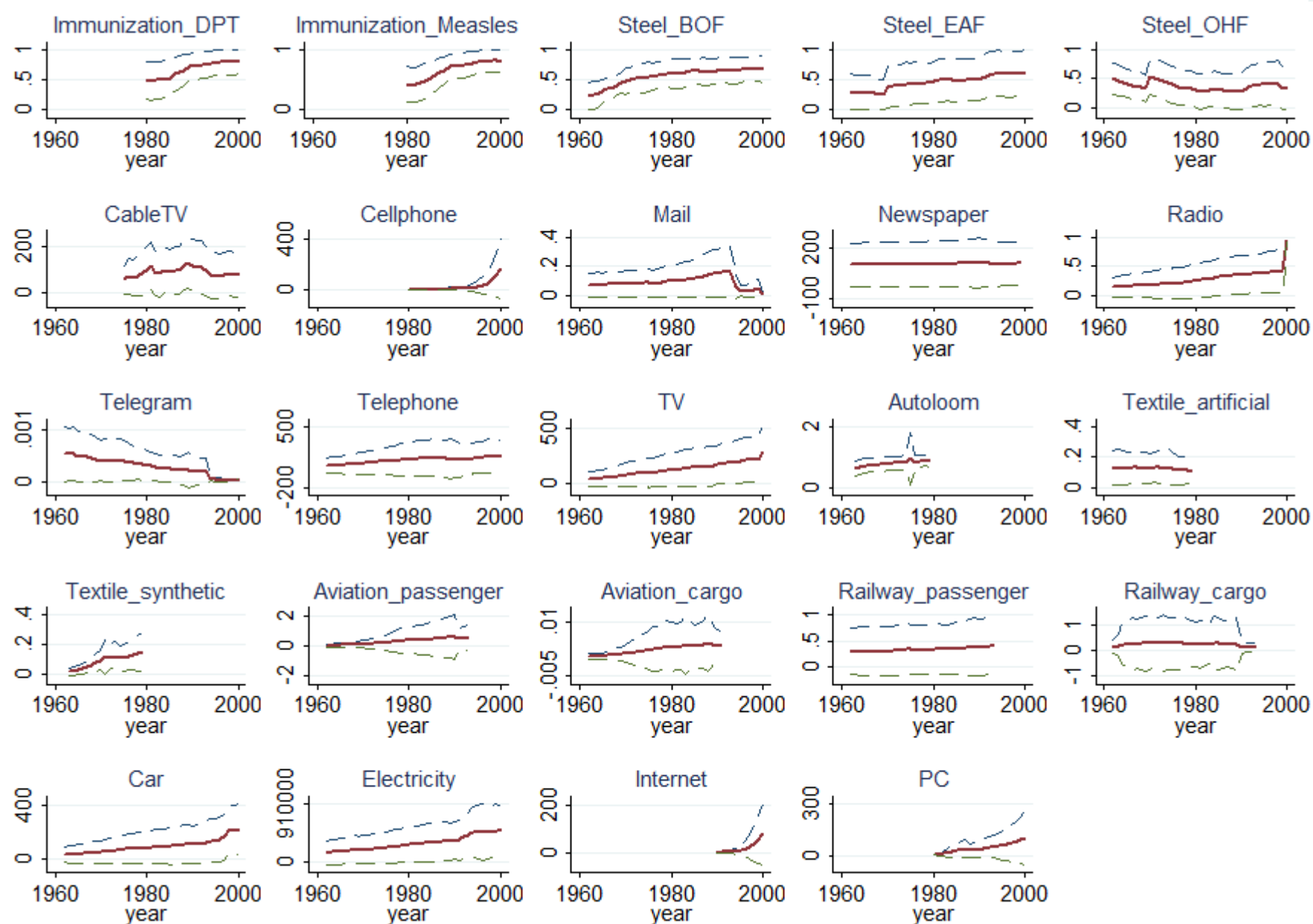
**Figure 2.**



**Figure 3.**

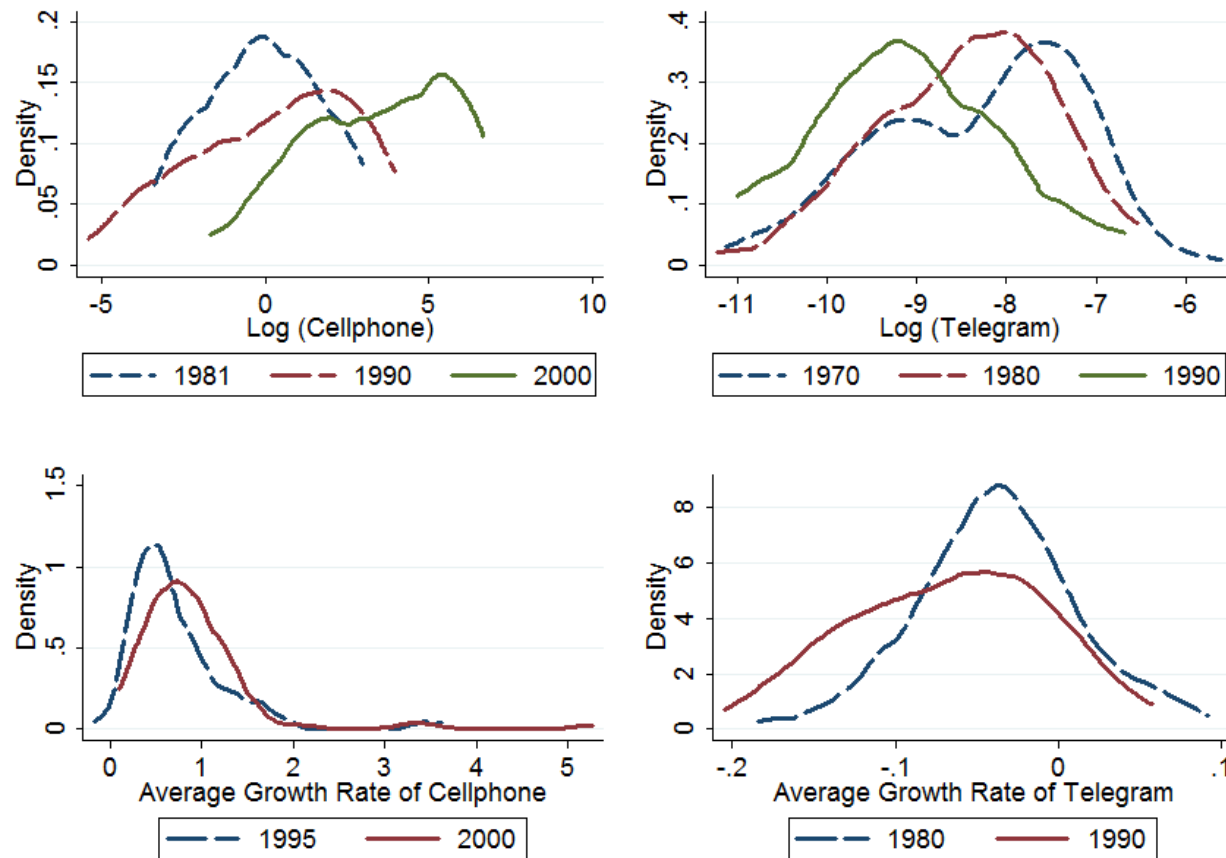


**Figure 4. Cross-country average technology intensity levels.** The number of countries may vary across different technologies and different years.





**Figure 5. Estimates of the distribution of countries according to log intensity levels and average growth rates of cellphone and telegram.** The figure below shows that, for both the log level and average growth rate measures, the relatively new technology “Cellphone” has distributions shifting rightward over time while the relatively old technology “Telegram” has distributions shifting leftward over time. For “Cellphone” on the bottom left, the growth rate in 1995 refers to the geometric average of the growth rates between 1990 and 1995 and the growth rate in 2000 refers to the average between 1995 and 2000. For “Telegram” on the bottom right, the growth rate in 1980 refers to the average between 1970 and 1980 and the growth rate in 1990 refers to the average between 1980 and 1990.



**Table 1. Merging trade data for historical unification or fragmentation.**

Country Name after Merging	Russia		Germany		Yemen		Czech Republic	
Country Name before Merging	Former USSR	Russia	Former German FR	Germany	Former Yemen Dm	Yemen	Czechoslovakia	Czech Republic
Merging Periods	1962- 1991	1992- 2000	1962- 1990	1991- 2000	1962- 1990	1991- 2000	1962-1992	1993- 2000

**Table 2. Intensity variables and descriptions for the technologies examined.**

INTENSITY VARIABLES	VARIABLE DESCRIPTION
<i>I. HEALTH</i>	
1. Immunization_DPT	Percent of children aged 12-23 months who received a DPT (diphtheria, pertussis, and tetanus) immunization (including all three doses) before the age of one year
2. Immunization_measles	Percent of children aged 12-23 months who received a measles immunization (one dose only) before the age of one year
<i>II. STEEL</i>	
3. Steel_BOF	Fraction of crude steel production (in metric tons) in blast oxygen furnaces (a process that replaced Bessemer and OHF processes)
4. Steel_EAF	Fraction of crude steel production (in metric tons) in electric arc furnaces (a process that complemented and improved upon Bessemer and OHF processes)
5. Steel_OHF	Fraction of crude steel production (in metric tons) in open hearth furnaces (a process that complemented the Bessemer process)
<i>III. TELECOM</i>	
6. CableTV	Number of households that subscribe to a multi-channel television service delivered by a fixed line connection per capita
7. Cellphone	Number of users of portable cell phones per capita
8. Mail	Number of items mailed/received per capita
9. Newspaper	Number of newspaper copies circulated daily per capita
10. Radio	Number of radios per capita
11. Telegram	Number of telegrams sent per capita
12. Telephone	Number of mainline telephone lines connecting a customer's equipment to the public switched telephone network as of year end per capita
13. TV	Number of television sets in use per capita
<i>IV. TEXTILES</i>	
14. Autoloom	Fraction of operable looms (of a certain size) in place at year end that are either automatic or have automatic attachments (as opposed to ordinary looms)
15. Textile_artificial	Fraction of weight of fibers used in spindles that are artificial (cellulosic)
16. Textile_synthetic	Fraction of weight of fibers used in spindles that are synthetic (non-cellulosic)
<i>V. TRANSPORTATION</i>	
17. Aviation_passenger	Civil aviation passenger-KM traveled on scheduled services by companies registered in the country concerned per capita
18. Aviation_cargo	Civil aviation ton-KM of cargo carried on scheduled services by companies registered in the country concerned per unit of real GDP
19. Railway_passenger	Passenger journeys by railway in passenger-KM per capita
20. Railway_cargo	Ton-KM of freight carried on railways (excluding livestock and passenger baggage) per unit of real GDP
21. Car	Number of passenger cars (excluding tractors and similar vehicles) in use per capita
<i>VI. GENERAL</i>	
22. Electricity	Gross output of electric energy (inclusive of electricity consumed in power stations) in KwHr per unit of real GDP
23. Internet	Number of people with access to the worldwide network per capita
24. PC	Number of self-contained computers designed for use by one person per capita

**Table 3a. Fixed-effects regressions results (health, steel, and telecommunication).** Robust standard errors are in italics. Significance levels: \*10%, \*\*5%, and \*\*\*1%. Definitions of dependent variables can be found in Table 2.

	HEALTH		STEEL			TELECOMMUNICATION							
	DPT	Measles	BOF	EAF	OHF	CableTV	Cellphone	Mail	Newspaper	Radio	Telegram	Telephone	TV
RGDP	-.01222	.06148***	-.01581	-.05403**	-.1510***	2.33593***	.26939	.80252***	.24854***	-.02059	.12862*	1.34210***	.40862***
	<i>.01745</i>	<i>.01809</i>	<i>.02278</i>	<i>.02093</i>	<i>.03426</i>	<i>.34707</i>	<i>.30736</i>	<i>.04129</i>	<i>.02721</i>	<i>.03034</i>	<i>.06630</i>	<i>.03167</i>	<i>.06502</i>
Openness	.00130	-.01226	.12746***	.12109***	-.06255	-.33559	-.20430	.07932	-.02748	-.09364**	-.15990	.49431***	-.07725
	<i>.01537</i>	<i>.01560</i>	<i>.03695</i>	<i>.02835</i>	<i>.06039</i>	<i>.31258</i>	<i>.20975</i>	<i>.06473</i>	<i>.03666</i>	<i>.04048</i>	<i>.09804</i>	<i>.04478</i>	<i>.08172</i>
TW	.20055***	.12094***	.20383***	.12718***	.13460***	.30369***	1.25208***	.02327**	.05317	.62181***	.45238***	-.17738***	1.63607***
	<i>.02248</i>	<i>.01854</i>	<i>.01197</i>	<i>.01591</i>	<i>.00923</i>	<i>.07154</i>	<i>.02389</i>	<i>.01158</i>	<i>.04341</i>	<i>.04114</i>	<i>.01712</i>	<i>.01916</i>	<i>.05139</i>
D	-.0917***	-.0971***	-.00697*	-.00676*	-.00009	.10646***	-.19299***	.08480***	-.03776***	-.22348***	.18041***	-.14827***	-.25011***
	<i>.00405</i>	<i>.00433</i>	<i>.00392</i>	<i>.00383</i>	<i>.00906</i>	<i>.01503</i>	<i>.02479</i>	<i>.01199</i>	<i>.00809</i>	<i>.00771</i>	<i>.01841</i>	<i>.00770</i>	<i>.01336</i>
Cons.	-.2668***	-.4221***	.62486***	.59129***	.95114***	-1.28884*	-5.87634***	-3.70841***	2.55339***	-3.54156***	-4.18649***	.68327***	-9.2321***
	<i>.04820</i>	<i>.05203</i>	<i>.04920</i>	<i>.06756</i>	<i>.11597</i>	<i>.76042</i>	<i>.56474</i>	<i>.07425</i>	<i>.28498</i>	<i>.07876</i>	<i>.12044</i>	<i>.09561</i>	<i>.23253</i>
Adj-R <sup>2</sup>	.7962	.7722	.7225	.8274	.8310	.8944	.9074	.9672	.9654	.8894	.8508	.9649	.8679
# Obs.	2243	2193	1238	1867	760	662	1191	1667	3753	3999	1611	3201	3776

**Table 3b. Fixed-effects regressions results (textile, transportation, and general).** Robust standard errors are in italics. Significance levels: \*10%, \*\*5%, and \*\*\*1%. Definitions of dependent variables can be found in Table 2.

	TEXTILE			TRANSPORTATION					GENERAL		
	Autoloom	Artificial	Synthetic	A_passenger	A_cargo	R_passenger	R_cargo	Car	Electricity	Internet	PC
RGDP	.32783***	-.01274	.07672***	1.46488***	.89251***	.41610***	-.59471***	1.04595***	-.04421	-.65484	1.19747***
	<i>.06991</i>	<i>.01499</i>	<i>.02417</i>	<i>.04020</i>	<i>.06417</i>	<i>.03963</i>	<i>.04141</i>	<i>.03696</i>	<i>.02936</i>	<i>.45472</i>	<i>.15767</i>
Openness	.08981	.04263*	.06253**	.37639***	.64112***	-.19427***	-.24577***	.10187**	.14111***	-.62580*	.40258***
	<i>.11301</i>	<i>.02475</i>	<i>.03066</i>	<i>.05511</i>	<i>.08234</i>	<i>.06395</i>	<i>.06596</i>	<i>.04965</i>	<i>.03954</i>	<i>.32657</i>	<i>.12823</i>
TW	-.12070	.03244**	-.00238	.50820***	.51098***	.14698***	.16658***	.36519***	.21230***	1.49682***	1.27181***
	<i>.10645</i>	<i>.01364</i>	<i>.00784</i>	<i>.02084</i>	<i>.02855</i>	<i>.05419</i>	<i>.02542</i>	<i>.03022</i>	<i>.02722</i>	<i>.03035</i>	<i>.03461</i>
D	-.01161*	.00293	-.03228***	-.04139***	-.03904***	.03940***	.10221***	-.09348***	-.17529***	-.14348***	.06602***
	<i>.00614</i>	<i>.00500</i>	<i>.00476</i>	<i>.00775</i>	<i>.01144</i>	<i>.01086</i>	<i>.01502</i>	<i>.00811</i>	<i>.00556</i>	<i>.01796</i>	<i>.01657</i>
Cons.	.15161	.21415***	-.34554***	-4.29637***	-5.25460***	-2.20504***	-1.12449***	-1.37283***	5.38322***	-4.77810***	-4.75594***
	<i>.10949</i>	<i>.04163</i>	<i>.05422</i>	<i>.08245</i>	<i>.25342</i>	<i>.08469</i>	<i>.10728</i>	<i>.13690</i>	<i>.37729</i>	<i>.70137</i>	<i>.25848</i>
Adj-R <sup>2</sup>	.3762	.7358	.6491	.9482	.8588	.9523	.9542	.9458	.8836	.9128	.9527
# Obs.	1017	963	813	2681	2419	2202	2430	3399	3973	877	1043

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Appendix A

**Table A1a. Fixed-effects regressions with education variables (health, steel, and telecommunication).** Robust standard errors are in italics. Significance levels: \*10%, \*\*5%, and \*\*\*1%. Definitions of dependent variables can be found in Table 2.

	HEALTH		STEEL			TELECOMMUNICATION							
	DPT	Measles	BOF	EAF	OHF	CableTV	Cellphone	Mail	Newspaper	Radio	Telegram	Telephone	TV
RGDP	-.01222	.06148	.26516**	-.2191**	-.31644**	2.33593***	.26939	.52374**	.30025**	.42426*	.12862	1.24969***	1.62966***
	.04652	.05857	.12196	.10565	.13637	.69950	.86908	.21299	.13498	.21679	.23709	.13211	.42920
Openness	.00130	-.01226	-.03404	.36869	-.06821	-.33559	-.20430	.35956*	.27297**	-.10482	-.15990	.12677	-.10334
	.03506	.02932	.20866	.23773	.19595	.46320	.37049	.21283	.13195	.12359	.23075	.20690	.47741
Primary			-.08572	.03720	-.4098**			-.08289	.27491	.27434		.56707***	1.19719**
			.13025	.10904	.18463			.29180	.18858	.26018		.18009	.54435
Secondary			.03125	.10142	-.14170			-.00851	-.04741	.13373		.61572***	.16277
			.06323	.10971	.09046			.14492	.11569	.13415		.10906	.30951
TW	.20055***	.12094**	.14596***	.07685*	.10828**	.30369	1.25208***	.05828	.01021	.46407**	.45238***	-.19484***	1.15373***
	.05402	.04693	.03628	.04477	.03958	.18780	.06587	.09592	.11406	.18138	.08333	.05537	.29133
D	-.0917***	-.0971***	.01872**	-.01716	.03571	.10646***	-.19299***	.07749*	.00907	-.06715***	.18041***	-.06740***	-.09084**
	.00893	.01032	.00793	.02043	.02285	.02633	.03726	.04036	.02708	.02180	.05285	.01343	.03414
Cons.	-.2668**	-.4221***	.43724	.43763**	1.99712***	-1.28884	-5.8763***	-3.3698***	3.63217***	-2.9455***	-4.18649***	1.53155***	-6.81992***
	.10695	.13562	.27715	.21314	.25194	1.33082	1.26986	.41606	.70062	.38979	.57896	.28520	1.27677
Adjusted R-squared	.7962	.7722	.7689	.8596	.8614	.8944	.9074	.9739	.9612	.9291	.8508	.9872	.8928
# Obs.	2243	2193	495	669	457	662	1191	985	1349	1385	1611	1289	1319

**Table A1b. Fixed-effects regressions with education variables (textile, transportation, and general).** Robust standard errors are in italics. Significance levels: \*10%, \*\*5%, and \*\*\*1%. Definitions of dependent variables can be found in Table 2.

	TEXTILE			TRANSPORTATION					GENERAL		
	Autoloom	Artificial	Synthetic	A_passenger	A_cargo	R_passenger	R_cargo	Car	Electricity	Internet	PC
RGDP	.34194**	-.05327	.07767	1.80236***	.89251***	.39349***	-.59471***	1.04595***	.16440	-.65484	1.19747***
	<i>.13667</i>	<i>.03916</i>	<i>.06495</i>	<i>.30834</i>	<i>.22361</i>	<i>.12064</i>	<i>.13933</i>	<i>.25524</i>	<i>.13657</i>	<i>.80401</i>	<i>.36205</i>
Openness	.18963	.07780*	.11708	.46617***	.64112***	-.03871	-.24577	.10187	.19052	-.62580	.40258
	<i>.12271</i>	<i>.04609</i>	<i>.09820</i>	<i>.17336</i>	<i>.20879</i>	<i>.20877</i>	<i>.17840</i>	<i>.14564</i>	<i>.15305</i>	<i>.53539</i>	<i>.42574</i>
Primary	-.12546	-.10119	-.01610	.05036		-.00625			.71352***		
	<i>.18249</i>	<i>.08743</i>	<i>.10450</i>	<i>.29230</i>		<i>.31871</i>			<i>.18793</i>		
Secondary	.04324	.05019	-.04618	.17860		.13749			.44799***		
	<i>.09550</i>	<i>.04129</i>	<i>.04120</i>	<i>.14773</i>		<i>.15077</i>			<i>.11031</i>		
TW	-.12792	.00162	-.00477	.40734***	.51098***	.05586	.16658***	.36519***	.20818	1.49682***	1.27181***
	<i>.15590</i>	<i>.02651</i>	<i>.01384</i>	<i>.10960</i>	<i>.06885</i>	<i>.21065</i>	<i>.05976</i>	<i>.09938</i>	<i>.19670</i>	<i>.05826</i>	<i>.08286</i>
D	-.00798*	.00493	-.03627***	-.02695**	-.03904**	.07325**	.10221***	-.09348***	-.06704***	-.14348***	.06602*
	<i>.00442</i>	<i>.00763</i>	<i>.00954</i>	<i>.01335</i>	<i>.01538</i>	<i>.0295</i>	<i>.03719</i>	<i>.01774</i>	<i>.01318</i>	<i>.02741</i>	<i>.03650</i>
Cons.	.10887	.26296**	-.38217**	-5.16701***	-5.25460***	-1.86578***	-1.12449***	-1.37283***	7.01127***	-4.77810***	-4.75594***
	<i>.19455</i>	<i>.10646</i>	<i>.15058</i>	<i>.57409</i>	<i>.70119</i>	<i>.36067</i>	<i>.35610</i>	<i>.52068</i>	<i>2.37823</i>	<i>1.26668</i>	<i>.89632</i>
Adjusted R-squared	.3651	.7558	.6220	.9551	.8588	.9645	.9542	.9458	.9363	.9128	.9527
# Obs.	837	818	703	1204	2419	1133	2430	3399	1381	877	1043

## Appendix B



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I certify that Zhen Zhu did at least 51% of the work for the coauthored paper, "Technology Diffusion on the International Trade Network," and Zhen Zhu is therefore listed as the first author of the paper.

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## **IV. CHAPTER 3**

### **LEARNING ON NETWORKS**

#### **4.1 Introduction**

Learning refers to the process of acquiring modifications in existing knowledge, skills, habits, or tendencies through experience, practice, or exercise (Merriam-Webster Dictionary). A major type of learning is social learning, which takes place through social interactions among human agents. For example, students update their knowledge by interacting with a teacher and classmates. More generally, it is a social learning process through which people collect information from others to make better decisions or simply to be better informed. Due to its economic components such as strategic behavior and information aggregation, social learning has been studied extensively in the recent economics literature (Banerjee, 1992; Bikhchandani, Hirshleifer and Welch, 1992, 1998; Gaviria and Raphael, 2001; Morris and Shin, 2002; Munshi, 2004). To a large extent, the analytical framework applied to social learning is also applicable to other learning processes among nonhuman agents such as firms, countries, or even animals. For example, technology diffusion among firms or countries can be well depicted as a learning process since the agents upgrade the quality of existing technology or start to adopt a new technology after observing others' behaviors and consequences. In the case of animals, the agents learn from each other's experience and evolve through the natural selection, which was captured long before by the idea of Darwinism.

Networks serve as a powerful tool to analyze the interactions among agents. Briefly speaking, a network is a collection of nodes and links. Each node represents an agent and each link represents a relationship between a pair of agents. For human agents, the link can be

interpreted as interpersonal relationships such as friendship. For technology diffusion among countries, the link can be trade, FDI, or patent license agreements.

In this chapter, learning is carried out on the networks. The learning process is defined by a naïve learning algorithm implemented by every agent. At the initial stage, the agents living on the networks are endowed with distinct knowledge stocks. In every new period, each agent updates its knowledge stock by taking weighted average of its own level and all other agents' levels from previous period. As a result of this simple learning algorithm, each agent's knowledge stock obtains the highest level in the limit. This chapter also investigates two obstructions to the learning process. First, the learning process can be obstructed if the agents put too much weight on themselves. By deploying the learning process on a complete network and varying the value of agents' self-weighting parameter, I can manipulate the speed of convergence. Section 4.2 provides the detailed analysis and the simulation results. Second, the learning process can be obstructed if the agents take into account the distances to others on the network. A special class of networks, square lattice, is used to study the distance effect on the learning process. Section 4.3 introduces some basic yet important network properties of square lattice. Section 4.4 investigates the distance effect on the learning process and provides the simulation results. Finally, Section 4.5 concludes the chapter.

## **4.2 Basic Learning Model**

### **4.2.1 The Building Blocks**

A finite set of agents  $N = \{1, 2, \dots, n\}$  live on a network. Their knowledge stocks are represented by an  $n \times 1$  vector  $\mathbf{k}^t = (k_1^t, k_2^t, \dots, k_n^t)^T$ , where  $k_i^t$  is agent  $i$ 's knowledge stock at time  $t$  and  $k_i^t \in [0, 1]$ <sup>31</sup> for  $i \in N$ .

An  $n \times n$  nonnegative matrix  $\mathbf{P}^t$  is called the influence matrix. For all  $i, j \in N$ ,  $P_{ij}^t \in [0, 1]$  is the influence weight that agent  $i$  places on agent  $j$ 's knowledge stock at time  $t$ . Notice that matrix  $\mathbf{P}^t$  is not necessarily symmetric, that is,  $P_{ij}^t$  does not have to equal  $P_{ji}^t$ .

The influence matrix is row-stochastic so that:

$$\sum_{j=1}^n P_{ij}^t = 1 \text{ and } P_{ij}^t \geq 0, \text{ for all } i, j \in N, \text{ and for all } t. \quad (1)$$

#### 4.2.2 The Initial Conditions

At time 0, each agent's knowledge stock is drawn independently from the uniform distribution over  $[0, 1]$ . That is:

$$k_i^0 \sim U(0, 1), \text{ for all } i \in N, \quad (2)$$

The influence matrix  $\mathbf{P}^0$  at time 0 can be any arbitrary nonnegative matrix satisfying the row-stochastic condition<sup>32</sup>.

#### 4.2.3 The Naïve Learning Algorithm

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<sup>31</sup> Note that this bounded set has maximum 1 and minimum 0. Therefore,  $k$  can be interpreted as the learning outcome measured in percentage. For example, if the agents are students,  $k$  can be interpreted as percentage course grade. If the agents are countries, among which technology diffusion takes place,  $k$  can be considered as percentage technology intensity.

<sup>32</sup>  $\mathbf{P}^0$  doesn't matter because the naïve learning algorithm described below doesn't depend on  $\mathbf{P}^0$ .

In every new period, the agents update their knowledge stocks by taking weighted average of all agents' knowledge stocks, including its own stock, from previous period. The key thing here is to determine how much weight should be assigned to each agent, including the agent itself. In the basic learning model, I follow the French-DeGroot mechanism (French, 1956; DeGroot, 1974) and assume that each agent has full access to any other agent. In the language of networks, this situation can be described as a complete network, where there exists a link between any two nodes. However, the naïve learning algorithm proposed here differs from the French-DeGroot mechanism in important ways, which can be described as follows:

$$w_{ij}^t = \begin{cases} \max(k_j^t - k_i^t, 0) & \text{for all } i, j \in N, j \neq i \\ \bar{s} & \text{for } j = i; \bar{s} > 0 \end{cases} \quad (3)$$

The above learning algorithm can be interpreted as the follow-the-best strategy. That is the agents only put weights on those who have knowledge stocks higher than their own stocks and the magnitude of the weight depends on how big the stock difference is. At the same time, they don't put any weight on those who have knowledge stocks lower than or equal to their own stocks. Finally,  $\bar{s}$  is the self-weighting parameter, which measures the influence from the existing knowledge.

The updated influence is hence the following:

$$p_{ij}^{t+1} = \begin{cases} \frac{w_{ij}^t}{\bar{s} + \sum_{h \in N_{-i}} w_{ih}^t}, & \text{for all } i, j \in N, j \neq i \\ \frac{\bar{s}}{\bar{s} + \sum_{h \in N_{-i}} w_{ih}^t}, & \text{for all } i, j \in N, j = i \end{cases} \quad (4)$$



where  $N_{-i}$  is the set of agents except agent  $i$ .

After updating the influence matrix  $\mathbf{P}^{t+1}$ , the agents further update their knowledge stocks as follows:

$$\mathbf{k}^{t+1} = \mathbf{P}^{t+1} \mathbf{k}^t, \text{ for } t \geq 0 \quad (5)$$

#### 4.2.4 Analytical and Simulation Results

Since the agents only put weights on themselves and those with relatively higher knowledge stocks, it can be expected that all the agents' knowledge stocks will conform to the highest initial endowment in the limit. Before I prove that this is indeed the case, I need to define the concepts of convergence and conformity.

**Definition 1** A vector sequence  $\{\mathbf{k}^t\}_{t=1}^\infty$  is convergent if  $\lim_{t \rightarrow \infty} \mathbf{k}^t$  exists, i.e., there exists  $\mathbf{k}^* \in \mathbb{R}^n$  s.t. for all  $\epsilon > 0$ , there exists  $t^* > 0$  s.t.  $\|\mathbf{k}^t - \mathbf{k}^*\| \leq \epsilon$  for  $t > t^*$ , where for a  $1 \times n$  vector  $\mathbf{x}$ ,  $\|\mathbf{x}\| = \sum_{i=1}^n x_i^2$  is defined as its norm.

**Definition 2** A vector sequence  $\{\mathbf{k}^t\}_{t=1}^\infty$  is conforming if there exists  $k^* \in \mathbb{R}$  s.t. for all  $\epsilon > 0$ , there exists  $t^* > 0$  s.t.  $|k_i^t - k^*| \leq \epsilon$  for  $t > t^*$  and for all  $i \in N$ .

It follows immediately after the definitions above that conformity is a stronger condition than convergence. Essentially, conformity of a vector can be restated as that all elements of the vector converge to the same value in the limit.

**Theorem 1** With the naïve learning algorithm defined in (3), (4), and (5),  $\{\mathbf{k}^t\}_{t=1}^\infty$  is conforming for all  $\mathbf{k}^0$  satisfying (2) and all  $\mathbf{P}^0$  satisfying the nonnegative and the row-stochastic conditions. Furthermore, the value conformed is the maximum element of  $\mathbf{k}^0$ .

**Proof** Denote the maximum element of  $\mathbf{k}^0$  as  $k_m$ . Therefore agent  $m$  is endowed with the highest knowledge stock initially. According to the naïve learning algorithm, agent  $m$  only puts weight on itself. Thus agent  $m$  sticks with  $k_m$  forever. Denote an agent other than  $m$  as  $k_r$ . Suppose at time  $t$ ,  $k_r^t < k_m^t$ ,  $k_r^{t+1} = \sum_{i=1}^n P_{ri}^t k_i^t > \sum_{i=1}^n P_{ri}^t k_r^t = k_r^t$ . Therefore,  $k_r^{t+1} > k_r^t$  if  $k_r^t < k_m^t$ . This process will continue until  $k_r^t = k_m^t$ . It is straightforward to see that the same conclusion holds if there are multiple maxima in  $\mathbf{k}^0$ . **Q.E.D.**

Although the conformity condition is guaranteed by the naïve learning algorithm, the speed of conformity can vary greatly if I impose different values for  $\bar{s}$ . The simulation results are shown in Figure 1.

[Insert Figure 1 here]

The results in Figure 1 confirm my hypothesis that the learning process can be obstructed if the agents put too much weight on themselves. In other words, the agents may be trapped by their initial endowments for quite a long time if they weight too much on the existing knowledge stocks. The intuition behind this is that, when acquiring new knowledge, the agents are likely to be constrained by their existing resources, which implicitly indicate their abilities.

### 4.3 Network Properties of the Square Lattice

One shortcoming of the basic model in Section 4.2 is that the analysis ignores a key feature of network structure, i.e., the distance between agents. Recall that in Section 4.2, each agent is granted with full access to all other agents on the network. This contradicts the observation that agents often have different levels of proximity to others. For example, in a

friendship network, people tend to have both close friends and normal acquaintance, or even someone they don't know but who is a friend of their friends. In the language of networks, an agent has both directly linked neighbors and indirectly linked neighbors' neighbors. It should be reasonable to assume that the agent is influenced more by directly linked neighbors than by those neighbors' neighbors. To add this dimension to my analysis, I need to utilize the concept of distance in the networks literature. The distance (also called geodesic distance) between any two agents on a network is defined as the shortest path between them. In other words, the distance between agent A and agent B should take the fewest steps to get from A to B or from B to A<sup>33</sup>.

To investigate the distance effect on the learning process, I focus on a special class of networks, square lattice. As described below, the concept of distance emerges naturally on a square lattice.

A square lattice (or square grid) is a two-dimensional spatial array formed by tiling the plane regularly with squares. The vertices of squares correspond with the nodes on the network while the sides of squares correspond with the links on the network. Figure 2 gives an example of  $3 \times 3$  square lattice.

[Insert Figure 2 here]

Due to its similarity to matrix, I can specify any node on a square lattice by calling its row number and column number. For example, denote the square lattice in Figure 2 as  $\mathbf{L}$ , then nodes A, B, and C can be denoted as  $L_{1,1}$ ,  $L_{2,1}$ , and  $L_{2,2}$ , respectively. This again follows the

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<sup>33</sup> Actually this argument is based on undirected networks. For directed networks, the distance between A and B may not be symmetric. That is the distance from A to B may differ from the distance from B to A.

notion of matrix in that the first number refers to row and the second number refers to column in the subscript.

Based on the degree of nodes, all nodes on the square lattice can be categorized into three groups, corner nodes, side nodes, and inner nodes. The corner node has degree of 2 (or 2 neighbors), the side node has degree of 3 (or 3 neighbors) and the inner node has degree of 4 (or 4 neighbors). Nodes A, B, and C in Figure 2 are examples of corner nodes, side nodes, and inner nodes, respectively. For any square lattice, the number of corner nodes is always fixed at 4 while the numbers for the other two types are increasing with the size of the square lattice.

Some important properties of square lattice follow immediately after the above definitions.

**Lemma 1** On a square lattice, the distance between node  $L_{m,n}$  and node  $L_{p,q}$  is  $|m - p| + |n - q|$ .

**Proof** Here I just provide the intuition without using strict mathematical language. Suppose I want to go from  $L_{m,n}$  to  $L_{p,q}$  on a square lattice, horizontally I have to move at least  $|m - p|$  steps while vertically I have to move at least  $|n - q|$  steps. Therefore, the distance between them should be  $|m - p| + |n - q|$ . **Q.E.D.**

**Theorem 2** On a  $n \times n$  square lattice, the average distance for node  $L_{m,n}$  is  $\frac{\sum_{i=1}^n \sum_{j=1}^n |i-m| + |j-n|}{n^2 - 1}$ .

**Proof** The numerator of the average distance follows Lemma 1 to sum up the distances between  $L_{m,n}$  and all other nodes. The denominator is the total number of nodes on the square lattice except  $L_{m,n}$ . **Q.E.D.**

Armed with Theorem 2, I can calculate the average distance for every node on the square lattice. An example is shown in Figure 3.

[Insert Figure 3 here]

As shown in Figure 3, the average distances on a square lattice has a nice bowl shape with the global minima<sup>34</sup> sitting on the center of the square lattice and the global maxima sitting on the corners.

#### 4.4 Learning on a Square Lattice

Now I can modify the naïve learning algorithm in Section 4.2 by taking into account the distances between agents on the square lattice.

##### 4.4.1 The Building Blocks

Again, a finite set of agents  $N = \{1, 2, \dots, n^2\}$  live on a network. The network is an  $n \times n$  square lattice. Each node on the square lattice is occupied by an agent. The agents' knowledge stocks are represented by an  $n^2 \times 1$  vector  $\mathbf{k}^t = (k_1^t, k_2^t, \dots, k_{n^2}^t)^T$ , where  $k_i^t$  is agent  $i$ 's knowledge stock at time  $t$  and  $k_i^t \in [0, 1]$  for  $i \in N$ .

An  $n^2 \times n^2$  nonnegative matrix  $\mathbf{P}^t$  is called the influence matrix. For all  $i, j \in N$ ,  $P_{ij}^t \in [0, 1]$  is the influence weight that agent  $i$  places on agent  $j$ 's knowledge stock at time  $t$ . Notice that matrix  $\mathbf{P}^t$  is not necessarily symmetric, that is,  $P_{ij}^t$  does not have to equal  $P_{ji}^t$ .

The influence matrix is row-stochastic so that:

$$\sum_{j=1}^{n^2} P_{ij}^t = 1 \text{ and } P_{ij}^t \geq 0, \text{ for all } i, j \in N, \text{ and for all } t. \quad (6)$$

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<sup>34</sup> For an  $n \times n$  square lattice, if  $n$  is an odd number, the global minimum is unique. If  $n$  is an even number, there are four global minima.

#### 4.4.2 The Initial Conditions

At time 0, there is one agent with the knowledge stock of 1. All other agents are endowed with 0 knowledge stock<sup>35</sup>.

The influence matrix  $\mathbf{P}^0$  at time 0 can be any arbitrary nonnegative matrix satisfying the row-stochastic condition.

#### 4.4.3 The Modified Learning Algorithm

In every new period, the agents update their knowledge stocks by taking weighted average of all agents' knowledge stocks, including its own stock, from previous period. The weight consists of two components. The first is the difference between agents' knowledge stocks. The second is the distance between agents. Denote the distance between agent  $i$  and agent  $j$  as  $d_{ij}$ :

$$w_{ij}^t = \begin{cases} \max(k_j^t - k_i^t, 0) \cdot \frac{1}{d_{ij}} & \text{for all } i, j \in N, j \neq i \\ \bar{s} & \text{for } j = i; \bar{s} > 0 \end{cases} \quad (7)$$

The updated influence is hence the following:

$$P_{ij}^{t+1} = \begin{cases} \frac{w_{ij}^t}{\bar{s} + \sum_{h \in N_{-i}} w_{ih}^t}, & \text{for all } i, j \in N, j \neq i \\ \frac{\bar{s}}{\bar{s} + \sum_{h \in N_{-i}} w_{ih}^t}, & \text{for all } i, j \in N, j = i \end{cases} \quad (8)$$

where  $N_{-i}$  is the set of agents except agent  $i$ .

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<sup>35</sup> The distance effect can be seen by placing the highest-knowledge-stock agent in different locations on the square lattice.

After updating the influence matrix  $\mathbf{P}^{t+1}$ , the agents further update their knowledge stocks as follows:

$$\mathbf{k}^{t+1} = \mathbf{P}^{t+1}\mathbf{k}^t, \text{ for } t \geq 0 \quad (9)$$

#### 4.4.4 The Simulation Results

Figure 4 shows the simulation results for the learning process with the highest-knowledge-stock agent at the northwest corner. Figure 5 shows the simulation results for the learning process with the highest-knowledge-stock agent at the middle of the north side. Finally, Figure 6 shows the simulation results for the learning process with the highest-knowledge-stock agent at the center.

[Insert Figures 4, 5, and 6 here]

Another way to look at the simulation results is to calculate the average knowledge intensity level of the lattice after certain periods. Table 1 reports the average knowledge intensity level after 100 periods for the three different scenarios.

[Insert Table 1 here]

Recall that the average distance on the square lattice has a nice bowl shape (Figure 3). The center node of the square lattice has the minimum average distance while the corner node of the square lattice has the maximum average distance. The (middle) side node's average distance

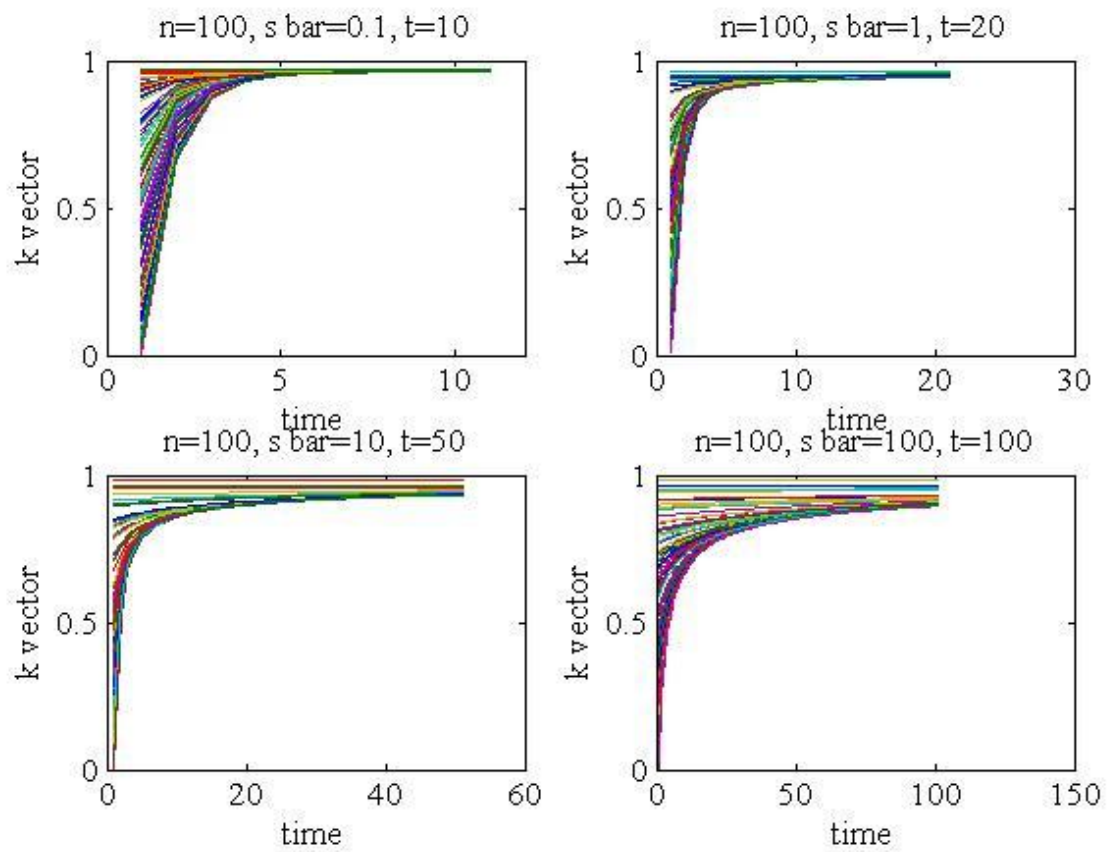
falls somewhere between the two extremes. Therefore, I can conclude from Table 1 that the diffusion process tends to be faster if it starts from a better-connected node on the square lattice.

## **4.5 Conclusion**

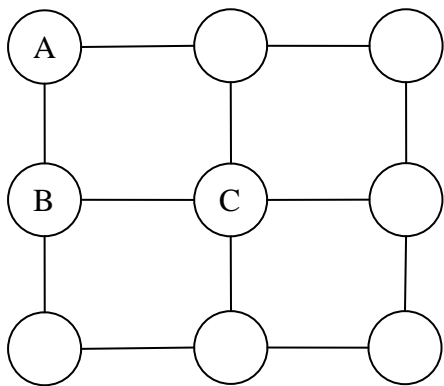
This chapter studies the learning process on networks. Initially, the agents living on the networks are assumed to have distinct knowledge stocks. A naïve learning algorithm is proposed to update agents' knowledge stocks over time. In every new period, each agent updates its knowledge stock by taking weighted average of its own level and all other agents' levels from previous period. As a result of this simple learning algorithm, each agent's knowledge stock obtains the highest level in the limit. This chapter also investigates two obstructions to the learning process. First, the learning process can be obstructed if the agents put too much weight on themselves. By deploying the learning process on a complete network and varying the value of the agents' self-weighting parameter, I can manipulate the speed of convergence. The convergence occurs sooner if the assigned self-weighting parameter is smaller. Second, the learning process can be obstructed if the agents take into account the distances to others on the network. A special class of networks, square lattice, is used to study the distance effect on the learning process. If only one agent is endowed with full knowledge stock of 1 and all others are endowed with zero knowledge stock in the initial period, the average knowledge stock on the whole network grows at the highest rate if the fully-stocked agent is placed in the center or at the lowest rate if the fully-stocked agent is placed in the corner.



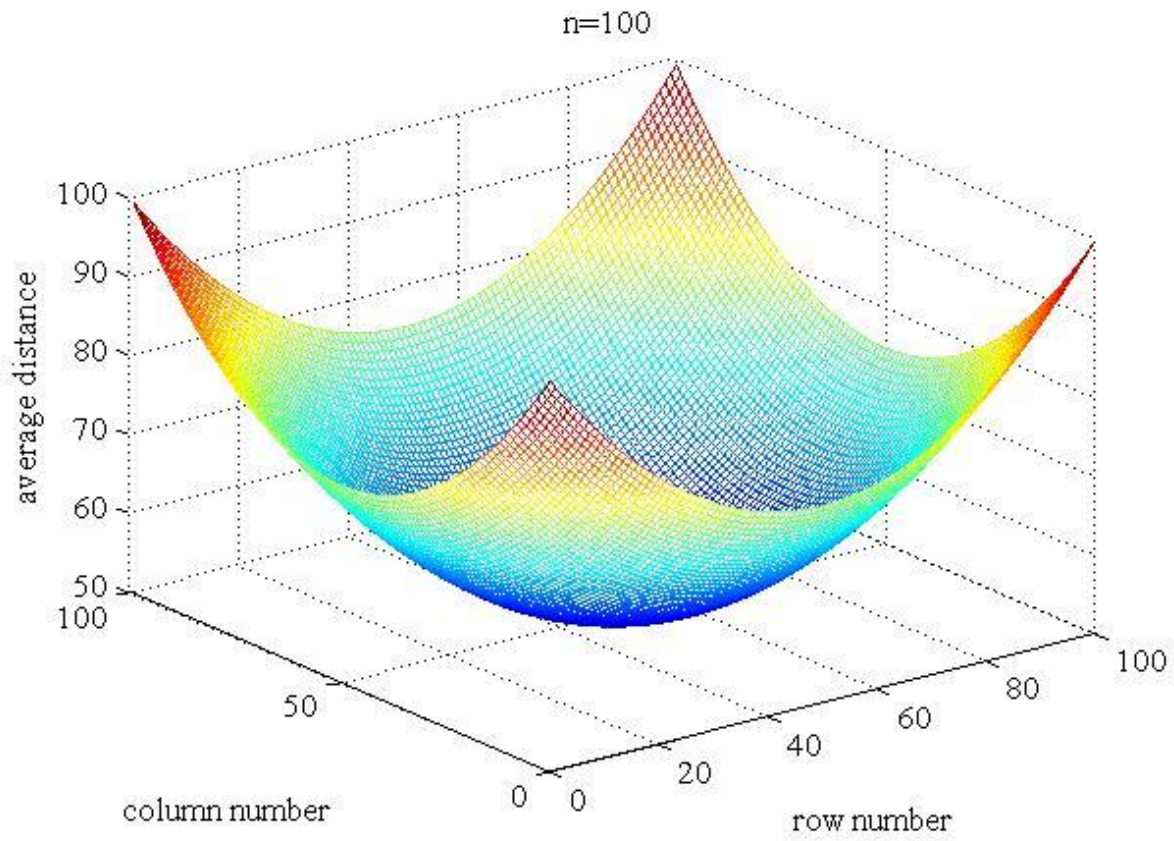
**Figure 1. Simulation results by varying the self-weighting parameter.**



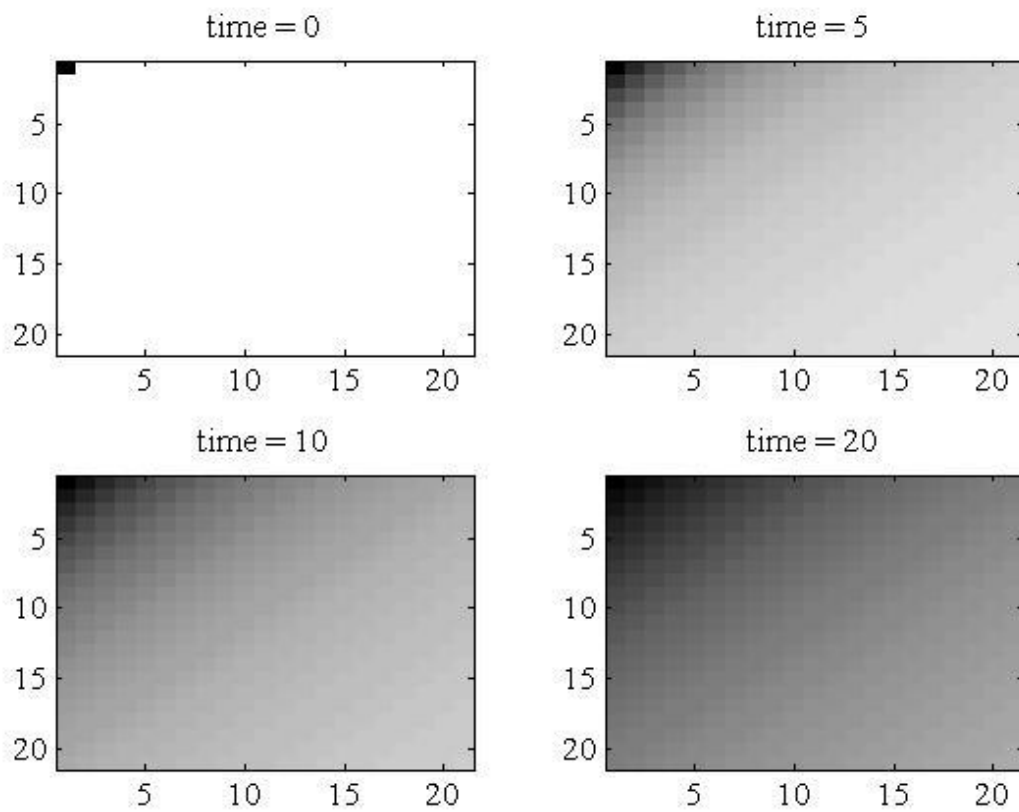
**Figure 2. An example of square lattice.**



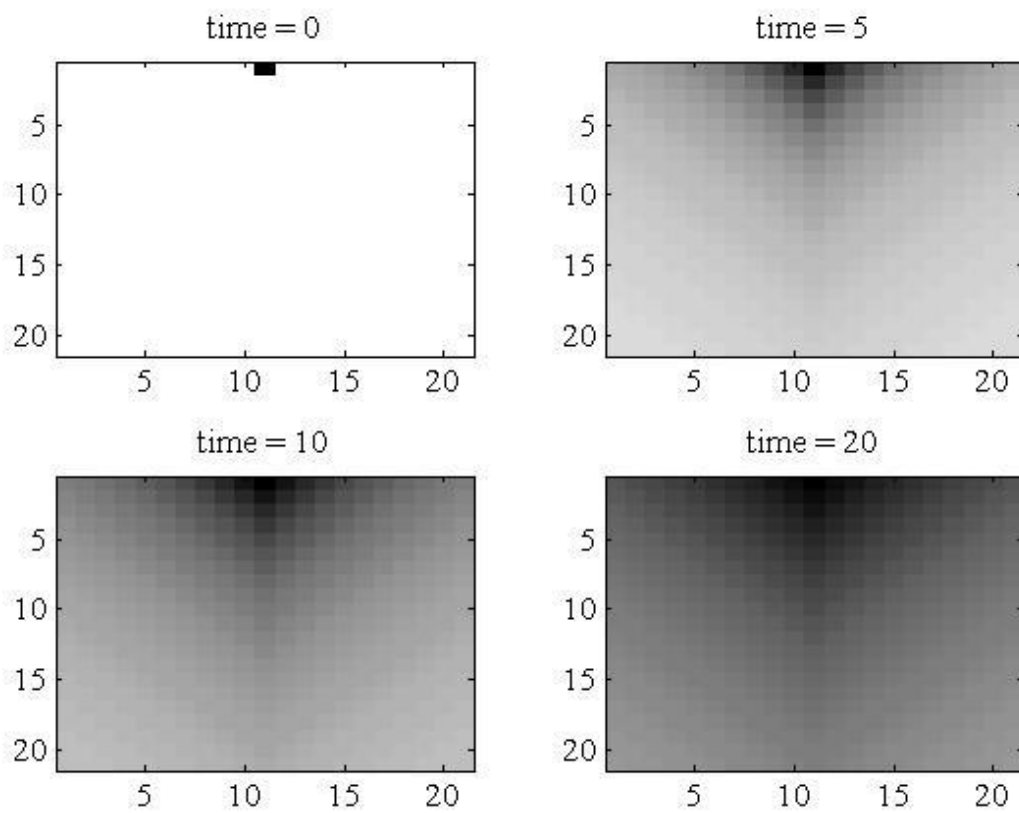
**Figure 3. The average distance on a square lattice ( $n=100$ ).**



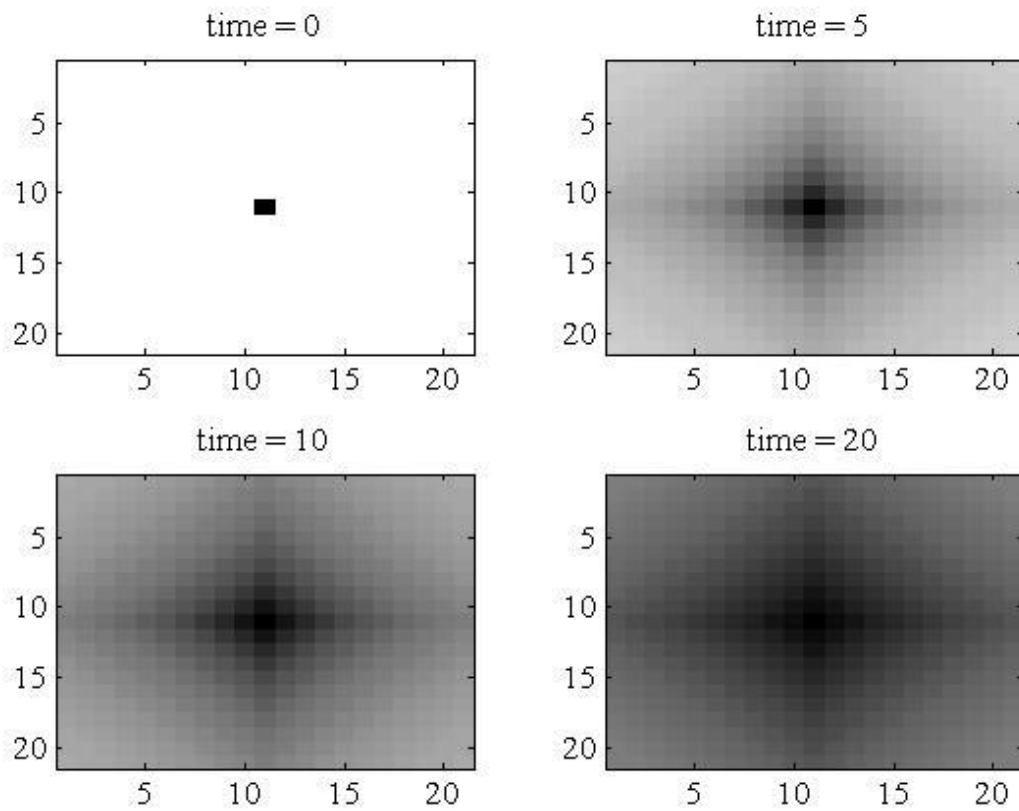
**Figure 4. Simulation results of the diffusion from the corner ( $\bar{s} = 1$ ;  $21 \times 21$  square lattice).**



**Figure 5. Simulation results of the diffusion from the side ( $\bar{s} = 1$ ;  $21 \times 21$  square lattice).**



**Figure 6. Simulation results of the diffusion from the center ( $\bar{s} = 1$ ;  $21 \times 21$  square lattice).**



**Table 1. The average knowledge intensity level after 100 periods.**

Starting Node	Average Knowledge Intensity After 100 Periods
Corner	0.8376
Side	0.8708
Center	0.9065

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## V. CONCLUSION

This dissertation explores two central components of the *Solow Residual* (or the *Total Factor Productivity*). One is an internally-driven productivity-enhancing process *within* an economy, the structural transformation. The other is an externally-driven productivity-enhancing process *between* economies, the technology diffusion.

It has been found that the micro decisions and the relationship structures matter in these productivity-enhancing processes. Chapter 1 identifies three driving forces behind China's structural transformation during the post-reform period 1978-2008. Chapter 1 also proposes a two-sector growth model with a micro feature of migration decision. After I calibrate the model with the real data and conduct the counterfactual exercises, the reduction of the migration costs can be shown as a significant contributor to China's structural transformation. Chapter 2 and 3 are devoted to the study of the technology diffusion. In Chapter 2, the trade effects on the technology diffusion are examined from a novel perspective: The international trade system can be viewed as a complex network. By controlling factors such as real GDP per capita, openness, and trade-share-weighted foreign technology levels, we still have significant results for the network distance variable. Our central finding is that the network structure matters in the technology diffusion process, i.e., the better-connected countries on the trade network tend not only to adopt new technologies faster but also to cast away old technologies faster. Finally, Chapter 3 is a theoretical approach to the technology diffusion and generalizes it as a learning process. By using the stylized learning models, Chapter 3 highlights two obstructions to the learning process. One is that the agents put too much weight on themselves when updating their



knowledge stocks and the other is that the agents are too far away from others in terms of the network distance.

Previous efforts in the field of growth economics have converged to a consensus that the traditional break-down of the factors of production is not be sufficient to answer the fundamental question of growth economics: Why have some countries achieved successful economic growth while others have failed? Answering the question requires deeper understanding of the mechanism that connects the macro variables. Perhaps the between-macro-and-micro networks approach is one way to go. The three essays in my dissertation have incorporated the idea of networks and are my first endeavors into opening the “black box” of the *Solow Residual*. With great interest and enthusiasm, I will continue this effort in my post-doctoral career.